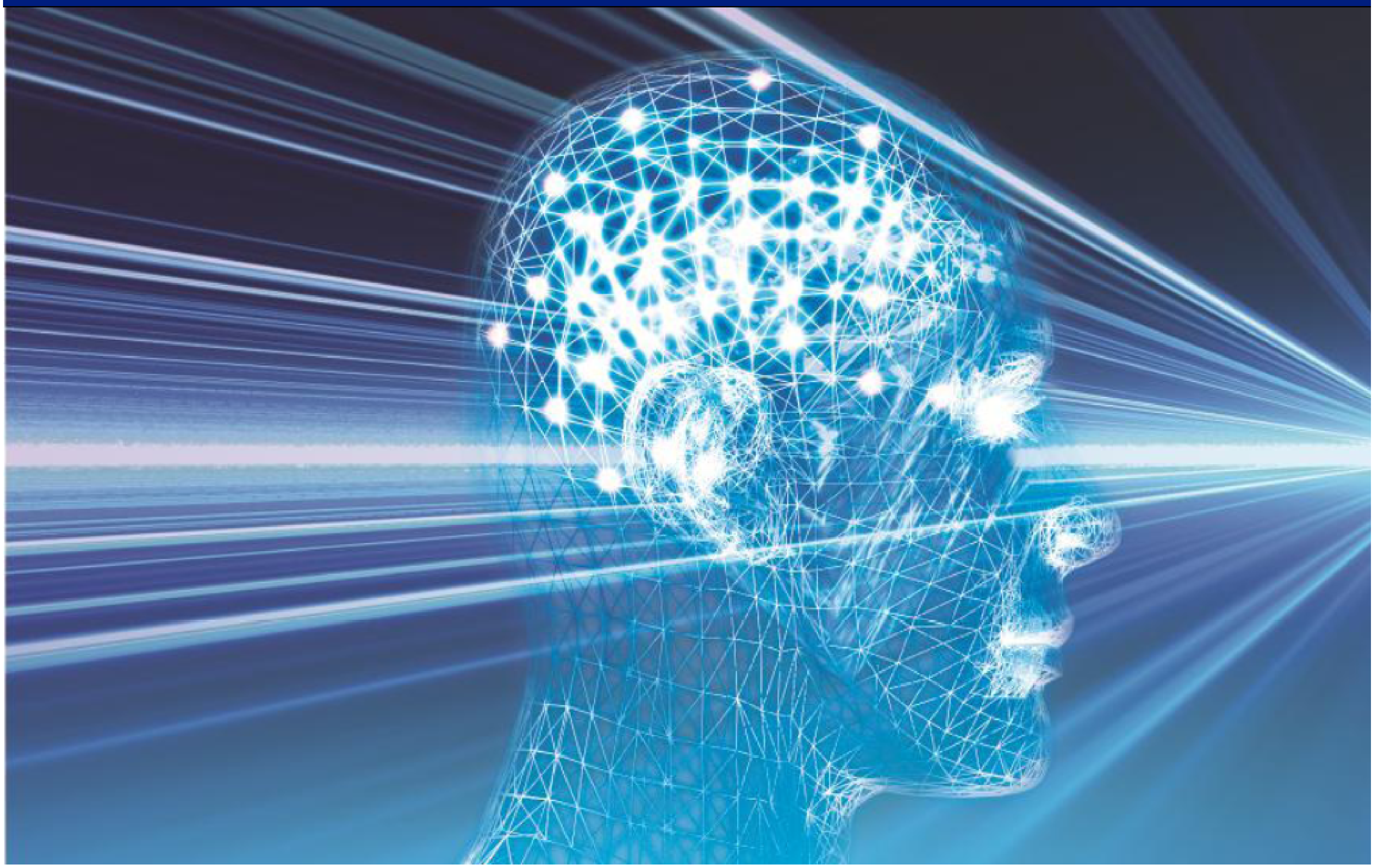
Natural Intelligence

The INNS Magazine

Volume 1, Issue 1, October 2011



Accounting for Creativity
Discovery of Concept Cells
Neural Networks Abstraction Capability
Early Detection of Alzheimer's Onset

INTERNATIONAL NEURAL NETWORK SOCIETY

Retail: US$10.00

INNS Officers and Board of Governors

2011 INNS Officers (Executive Committee)

President
Prof. Ron Sun
Rensselaer Polytechnic Institute
email: rsun@rpi.edu

Vice-President for Membership
Prof. Irwin King
Chinese University of Hong Kong
email: king@cse.cuhk.edu.hk

Vice-President for Conferences
Dr. Danil Prokhorov
TRINA
email: dvprokhorov@gmail.com

Treasurer
Prof. David Casasent
Carnegie Mellon University
email: casasent@ece.cmu.edu

Secretary
Prof. Jonathan Chan
King Mongkut's University of Technology Thonburi
email: jonathan@sit.kmutt.ac.th

2011 Board of Governors

Steven Bressler
Florida Atlantic University
email: bressler@fau.edu

Kenji Doya
Okinawa Institute of Science and Technology
email: doya@oist.jp

Prof. Fredric Ham
Florida Institute of Technology
email: fmh@fit.edu

Prof. Michael Hasselmo
Boston University
email: hasselmo@bu.edu

Prof. Nikola Kasabov
AUT
email: nkasabov@aut.ac.nz

Prof. Irwin King
Chinese University of Hong Kong
email: king@cse.cuhk.edu.hk

Prof. Robert Kozma
The University of Memphis
email: rkozma@memphis.edu

Derong Liu
Laboratory of Complex Systems
Email: derong.liu@gmail.com

Wolfgang Maass
Techn. Universitaet Graz
Email: maass@igi.tugraz.at

Prof. Risto Miikkulainen
University of Texas@Austin
email: risto@cs.utexas.edu

Prof. Ali Minai
University of Cincinnati
email: ali.minai@uc.edu

Prof. Francesco Carlo Morabito
University "Mediterranea" of Reggio Calabria
email: morabito@unirc.it

Prof. Klaus Obermayer
Technical University of Berlin
email: oby@cs.tu-berlin.de

Dr. Leonid Perlovsky
AFRL/SN
email: leonid.perlovsky@hanscom.af.mil

Stefan Schaal
University of Southern California
email: sschaal@usc.edu

Prof. Jennie Si
Arizona State University
Email: si@asu.edu

Marley Vellasco
Pontifícia Universidade Católica do Rio de Janeiro
E-mail: marley@ele.puc-rio.br

Ganesh Kumar Venayagamoorthy
Missouri University of Science and Technology
Email: gkumar@ieee.org

Prof. DeLiang Wang
Ohio State University
email: dwang@cse.ohio-state.edu

Dr. Lipo Wang
Nanyang Technological University
Email: elpwang@ntu.edu.sg

Jacek Zurada
University of Louisville
Email: jmzura02@louisville.edu

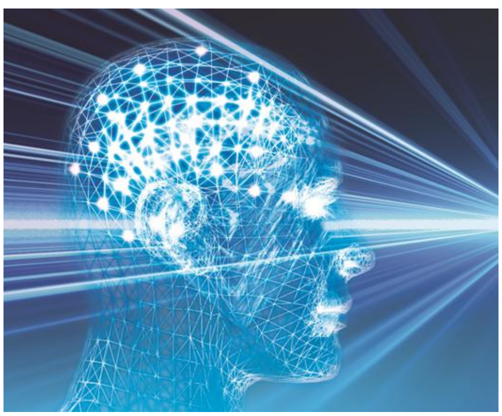
2011 INNS Committees

Nomination Committee Chair: Francesco Carlo Morabito
Award Committee Chair: Leonid Perlovsky
Government and Corporate Liaison Com. Chair: Ali Minai
Publication Committee Chair: Soo-Young Lee
Newsletter/Magazine Editor: Soo-Young Lee
Education Activities Committee Chair: Timo Honkela and Juyang (John) Weng

Natural Intelligence

The INNS Magazine

Volume 1, Issue 1, October 2011



Regular Papers

Columns

News

Reports

Call for Papers

Natural Intelligence: the INNS Magazine is published quarterly by the International Neural Network Society (INNS) at *www.inns.org* and *www.ni-inns.info*. **Headquarters**: 2424 American Lane, Madison, WI 53704, U.S.A. Telephone: +1-608-443-2461. Fax: +1-608-443-2474 or 1-608-443-2478. E-mail addresses: inns@reesgroupinc.com.
All submission should be made to *inns.ni@gmail.com* or *ni@neuron.kaist.ac.kr*.

Bridging Different Communities with the New INNS Magazine:

Soo-Young Lee
Editor-in-Chief, Natural Intelligence: the INNS Magazine

The International Neural Network Society (INNS) is launching a new magazine called "***Natural Intelligence***". The new INNS magazine aims at bridging different communities, spreading from neuroscientists to information engineers, and also from university students to world leading researchers.

Neural network research requires the integration of multidisciplinary effort. Neural network scientists are interested in learning about neural information processing mechanisms from neuroscience and cognitive science, computational models from mathematics and physics, electronic hardware and application-specific knowledge from electrical engineering and computer science, and so on. However, each academic discipline has its own way of studying and conducting research. In particular, neuroscientists and cognitive scientists use very different methodologies, which can make communication and collaboration more difficult. There is a need to bridge these communities. As the leading society of this interdisciplinary field, INNS is expected to fulfill the needs.

We define "Natural Intelligence" to include both "*intelligence existing in nature*" and "*intelligence based on the state of things in nature*". Therefore, the new INNS magazine "***Natural Intelligence***" plans to cover

- experiments
- computational models
- applications

of the intelligent functions in our brains.

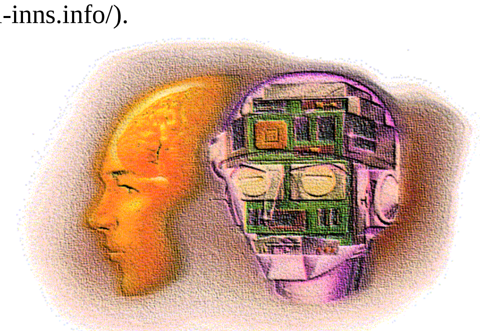
Also, there is an important need for well-written introductory papers targeting both young and established researchers from other academic backgrounds. The interdisciplinary nature of the many new emerging topics makes these introductory papers essential for research on Natural Intelligence. Therefore, the new INNS magazine will mainly publish

- review papers
- white papers
- tutorials.

In addition, columns, news, and reports on the communities will also be included.

Other magazines with similar goals exist in other disciplines, and these magazines enjoy high citation rates, impact factors, and excellent reputations. By publishing high-quality papers with a short review cycle, we believe that the new INNS magazine will join the list of high-impact publications while serving the neural network communities.

However, we need your help to achieve this goal. Please write and submit review papers, white papers, and tutorials. Also, you are always welcome to submit news and reports on special interest groups (SIGs), regional interest groups (RIGs), research programs, and conferences/workshops. All contributions should be submitted to the Editor-in-Chief by e-mail at **inns.in@gmail.com** or **ni@neuron.kaist.ac.kr**. Detail submission guidelines are shown at the Magazine homepages (http://www.inns.org and http://www.ni-inns.info/). ■



Beginning of a New Journey

Ron Sun
President of the International Neural Networks Society

The International Neural Networks Society (INNS) is embarking on a new journey. Not satisfied with its own past successes, INNS is constantly looking for new ways to better itself. The goal is for INNS to be the most prestigious professional organization in fields around neural networks and natural intelligence (broadly defined), as it has been for years. To keep up with the fast changing world of relevant science and technology, a new magazine that is designed to appeal to a broader readership ---the new INNS magazine entitled "***Natural Intelligence***"---thus is born.

For many years, INNS has been the important professional home for researchers and practitioners from all over the world who work in the broad areas of neural networks and natural intelligence. Over the years, the coverage and scope of INNS have become broader and deeper, as neural networks penetrate many more fields.

Indeed, over the years, the society has been covering many fields and areas, which include (among others):

- neuroscience,
- cognitive and psychological sciences,
- brain modeling,
- cognitive modeling,
- bioinformatics, neuroinformatics, and brain informatics,
- brain/mind-like computing,
- artificial neural networks,
- machine learning,
- pattern recognition, image processing, and vision,
- control theory and systems,
- application systems (for applications in science, engineering, business, and other areas),

and so on.

New research topics are also constantly emerging, including, for example,

- neurally and psychologically inspired robots,
- brain-computer interface,
- neural network models for social simulation and multi-agent systems,
- various types of hybrid systems,

and so on. In this regard, possibilities are almost limitless.

We are also continuing the development of INNS as a truly international, interdisciplinary, and broadly inclusive society. The diversity, openness, and all-encompassing nature of INNS is reflected in our resolve to develop and support topical sections (or SIGs) and regional chapters, especially in those fast developing regions of the world and in those fast developing fields, and to foster close collaboration with other professional societies.

As a pre-eminent professional organization, INNS works in close collaboration with a number of other professional organizations, such as the European Neural Network Society (ENNS), the Asia-Pacific Neural Network Assembly (APNNA), the IEEE Computational Intelligence Society, and many national societies (such as JNNS), as well as our own regional/national chapters.

Our flagship journal, *Neural Networks*, publishes state-of-art scholarly research work, with ever-broadening scope, in various areas of neural networks and natural intelligence. It has been a true asset for the research community.

Our flagship conference, *International Joint Conference on Neural Networks* (IJCNN), continues to be the premier venue for researchers and practitioners in these broad fields.

However, the Society is always looking for new opportunities for helping and supporting our communities. Recently, new regional chapters have been added or significantly expanded. New measures have been approved by the Board of Governors to strengthen the activities of regional chapters, topical sections, and special interest groups. For the sake of better serving our communities and to ensure that IJCNN remains a top-notch venue for the dissemination of new results in neural networks research, we also continue to look for new ways of improving its organization. Some of these new ways adopted by IJCNN include: several new, abstract-only submission categories; special day-long symposia, special tracks, especially special tracks for topical sections and some special interest groups, ….., and so on. A new winter conference series will also be organized that will become a truly international event, with highly regarded proceedings.

It is within the context of these exciting new developments, this new magazine is being launched, complementing and supplementing our flagship journal "Neural Networks". Compared with the journal, this new magazine will be more educational, more broad-based, more timely, and more appealing and informative for a broader readership.

Our goal, adopted by the Society, to better understand the human brain/mind and to create more powerful brain/mind-inspired intelligent machines for addressing complex problems faced by the 21st-century world is both challenging and exciting. With our joint efforts, we can make a significant difference in our future, and in particular the future of science and technology that benefit the humankind.

It is my honor to welcome all authors, readers, and editors to this new magazine. In particular, I am pleased that Professor Soo-Young Lee has accepted to be the inaugural editor-in-chief of this magazine. The success of the magazine will depend on all authors, readers, and editors. I am looking forward to seeing excellent reports, surveys, reviews, tutorials, and other articles appearing in this new publication.

The new journey has already begun. Please join us in our effort to shape our own professional, scientific, and technological future. ■

Accounting for Creativity using a Psychologically Realistic Cognitive Architecture

Sebastien Helie[1*] and Ron Sun[2]

[1] University of California Santa Barbara, USA
[2] Rensselaer Polytechnic Institute, USA
[*] *corresponding author*: sebastien.helie@psych.ucsb.edu

Abstract

This paper reviews a unified framework for understanding creative problem solving by using the CLARION cognitive architecture to derive the Explicit-Implicit Interaction (EII) theory. CLARION/EII constitutes an attempt at providing a more unified explanation of psychological phenomena by focusing on the co-existence of, the difference between, and the synergistic interaction of explicit and implicit processing. A list of key phenomena that can be accounted for by the EII theory and simulated using CLARION is presented. This work represents an initial step in the development of process-based theories of creativity encompassing incubation, insight, and various other related phenomena.

1. Introduction

Cognitive architectures are becoming increasingly ubiquitous in cognitive science and artificial intelligence (Langley, Laird, and Rogers 2009). Among the many architectures that have been proposed, the CLARION cognitive architecture (Sun 2002) focuses on trying to provide a more unified explanation of psychological phenomena using mostly five basic principles: 1) The co-existence of and the difference between explicit and implicit knowledge; 2) The simultaneous involvement of implicit and explicit processes in most tasks; 3) The "redundant" representation of explicit and implicit knowledge; 4) The integration of the results of explicit and implicit processing; and 5) The iterative (and possibly bidirectional) processing. This cognitive architecture has already been used to account for many psychological phenomena and simulate much relevant human data (see, e.g., Sun, Merrill, and Peterson 2001, Sun, Slusarz, and Terry 2005).

In relation to problem solving, many psychological theories of problem solving and reasoning have highlighted a role for implicit cognitive processes. For instance, implicit processes are often thought to generate hypotheses that are later explicitly tested (Evans 2006, Sun 1995). Also, similarity has been shown to affect reasoning through processes that are mostly implicit (Sun 1995). Yet, most theories of problem solving have focused on explicit processes that gradually bring the problem solver closer to the solution in a deliberative way. However, when an ill-defined or complex problem has to be solved (e.g., when the initial state or the goal state can lead to many different interpretations, or when the solution paths are highly complex), the solution is often found by sudden 'insight' (Bowden et al. 2005, Pols 2002), and regular problem solving theories are for the most part unable to account for this apparent absence of deliberative strategy.

A complementary line of research on creative problem solving has tried to tackle complex problem solving for many years. However, psychological theories of creative problem solving tend to be fragmentary and usually concentrate only on a subset of phenomena, such as focusing only on incubation (i.e., a period away from deliberative work on the problem; for a review, see Smith and Dodds 1999) or insight (i.e., the sudden appearance of a solution; for a review, see Pols 2002). The lack of detailed computational models has resulted in their limited impact on the field of problem solving (Duch 2006).

In this article, we review results obtained by using a psychologically realistic cognitive architecture, that is, CLARION, to develop an integrative theory of creative problem solving. The remainder of this article is organized as follows. First, we discuss the relevance of psychologically realistic cognitive architectures in artificial intelligence and cognitive science. Second, the Explicit-Implicit Interaction (EII) theory of creative problem solving is derived from the CLARION cognitive architecture. Third, we present a brief summary of phenomena that are captured by the EII theory and have been simulated by a CLARION-based computational model. This paper is concluded by a discussion of the advantages of using integrative frameworks in artificial intelligence and cognitive science.

2. Why are Cognitive Architectures Important?

A cognitive architecture is the overall essential structures and processes of a domain-generic computational cognitive model used for a broad, multiple-level, multiple-domain analysis of cognition and behavior (Sun 2004). Its function is to provide an essential framework to facilitate more detailed modeling and understanding of various components and processes of the mind. In this way, an architecture serves as an initial set of assumptions to be used for further development.

While there are all kinds of cognitive architectures in existence, this article focuses specifically on psychologically oriented cognitive architectures (as opposed to software engineering oriented "cognitive" architectures). For cognitive science, the importance of such cognitive architectures lies in the fact that they are beneficial to understanding the human mind. Researchers who use cognitive architectures must specify a cognitive mechanism in sufficient detail to allow the resulting models to be implemented on computers and run as simulations. While it is true that more specialized, narrowly scoped models may also serve this purpose, they are not as generic and as comprehensive.

For the fields of artificial intelligence (AI), the importance of cognitive architectures lies in the fact that they support the central goal of AI—Building artificial systems that are as capable as human beings. Cognitive architectures help us to reverse engineer the only truly intelligent system around—the human mind. The use of cognitive architectures in building intelligent systems may also facilitate the interaction between humans and artificially intelligent systems because of the similarity between humans and cognitively-based intelligent systems.

3. CLARION and EII

CLARION (Sun 2002, Sun et al. 2001, 2005) is an integrative cognitive architecture consisting of a number of distinct subsystems with a dual representational structure in each subsystem (implicit versus explicit representations). Its subsystems include the action-centered subsystem (the ACS), the non-action-centered subsystem (the NACS), the motivational subsystem (the MS), and the meta-cognitive subsystem (the MCS). The role of the action-centered subsystem is to control actions, regardless of whether the actions are for external physical movements or for internal mental operations. The role of the non-action-centered subsystem is to maintain general knowledge. The role of the motivational subsystem is to provide underlying motivations for perception, action, and cognition, in terms of providing impetus and feedback (e.g., indicating whether outcomes are satisfactory or not). The role of the meta-cognitive subsystem is to monitor, direct, and modify dynamically the operations of the other subsystems.

Given the length limit of this article, we cannot present a detailed mathematical/algorithmic description of the CLARION cognitive architecture. Instead, some of the most basic general principles are briefly introduced below. The reader interested in detailed specifications of the cognitive architecture is referred to the cited papers above.

3.1 Basic Principles

Principle #1: The Co-existence of, and the Difference Between, Explicit and Implicit Knowledge

The CLARION cognitive architecture assumes the existence of two different types of knowledge, namely explicit and implicit, residing in two separate modules (Sun 2002). Explicit knowledge is easier to access and verbalize, said to be often symbolic, crisper, and more flexible (Sun et al. 2001). However, using explicit knowledge requires more extensive attentional resources (Sun et al. 2005). In contrast, implicit knowledge is relatively inaccessible, harder to verbalize, often "subsymbolic", and often more specific, more vague, and noisier (Sun 2002). However, using implicit knowledge does not tap much attentional resources. As such, explicit and implicit knowledge is processed differently. In the CLARION cognitive architecture, explicit processes perform some form of rule-based reasoning (in a very generalized sense) and represent relatively crisp and exact processing (often involving hard constraints), while implicit processing is 'associative' and often represents soft-constraint satisfaction (Sun 1995, 2002).

Principle #2: The Simultaneous Involvement of Implicit and Explicit Processes in Most Tasks

Explicit and implicit processes are involved simultaneously in most tasks under most circumstances (Sun 2002). This can be justified by the different representations and processing involved with the two types of knowledge (see, e.g., Sun et al. 2005). As such, each type of processes can end up with similar or contradictory conclusions that contribute to the overall output.

Principle #3: The "Redundant" Representation of Explicit and Implicit Knowledge

In the CLARION cognitive architecture, explicit and implicit knowledge is often "redundant": it frequently amounts to a re-description of one another in different representational forms. For example, knowledge that is initially implicit is often later re-coded to form explicit knowledge (through "bottom-up learning"; Sun et al. 2001, Helie, Proulx, and Lefebvre 2011). Likewise, knowledge that is initially learned explicitly (e.g., through verbal instructions) is often later assimilated and re-coded into an implicit form, usually after extensive practice (top-down assimilation: Sun 2002). There may also be other ways redundancy is created, e.g., through simultaneous learning of implicit and explicit knowledge.

Principle #4: The Integration of the Results of Explicit and Implicit Processing

Although explicit and implicit knowledge are often re-descriptions of one another, they involve different forms of representation and processing, which may produce similar or different conclusions; the integration of these conclusions may be necessary, which may lead to synergy, that is, overall better performance (Sun et al. 2005).

Principle #5: The Iterative (and Possibly Bidirectional) Processing

Processing is often iterative and potentially bidirectional in the CLARION cognitive architecture. If the integrated outcome of explicit and implicit processes does not yield a definitive result (i.e., a result in which one is highly confident) and if there is no time constraint, another round of processing may occur, which may often use the integrated outcome as a new input. Reversing the direction of reasoning may sometimes carry out this process (e.g., abductive reasoning; Johnson and Krem 2001). Alternating between forward and backward processing has been argued to happen also in everyday human reasoning (Rips 1994).

3.2 The EII theory of creative problem solving

The CLARION cognitive architecture has recently been used to derive a new integrative theory of creative problem solving (Helie and Sun 2010). The EII theory constitutes an attempt at integrating, and thus unifying (to some extent), existing theories of creative problem solving in two senses. First, most theories of creative problem solving have focused on either a high-level stage decomposition (e.g., Wallas 1926) or on a process explanation of only one of the stages (Lubart 2001). Second, the process theories of incubation (e.g., Smith and Dodds 1999) and insight (e.g., Pols, 2002) are usually incomplete and often mutually incompatible. EII attempts to integrate the existing theories to provide a detailed description of the processes involved in key stages of creative problem solving. EII starts from Wallas' (1926) stage decomposition of creative problem solving and provides a detailed process-based explanation of each stage that is ready for a coherent computational implementation. However, EII is not just an integration/implementation of previously existing vague theories, but it is a new theory, which focuses on the importance of implicit processing and knowledge integration in problem solving. The EII theory relies on the five basic principles of CLARION, as explained above, plus a few (relatively minor) auxiliary principles.

In addition to the five principles of CLARION presented so far, three auxiliary principles necessary to account for creative problem solving should be mentioned. These principles are less important and alternative principles may be equally viable. Therefore they are not central to the fundamental theoretical framework of the EII theory. First, Principle #5 implies that a 'definitive result' needs to be achieved in order to terminate the iterative process. This stopping criterion assumes a primitive form of meta-cognitive monitoring that can estimate the probability of finding a solution (Bowers et al. 1990). In EII, this meta-cognitive measure is termed the *Internal Confidence Level* (ICL). Second, there must be a threshold that defines what is meant by 'definitive result'. This threshold can vary as a function of task demands, and there might be several thresholds for different levels of confidence (Bowers et al. 1990). Lastly, a negative relationship between the ICL and the psychological response time was assumed (Costermans, Lories, and Ansay 1992).

4. Creativity in Problem Solving

This section presents EII explanations and the corresponding CLARION-based simulation results for well-established psychological paradigms (e.g., free recall, lexical decision, and problem solving). Given the broad scope of this article, the emphasis cannot be on the fine-grained details involved. Detailed explanations and simulations can be found in Helie and Sun (2010).

4.1 Incubation in a Lexical Decision Task

Yaniv and Meyer (1987) showed human subjects word definitions that were weakly associated with their definiendums. The subjects had a limited time to find each definition's definiendum (the rare-word association task). If the subject found the definiendum, they were transferred to a lexical decision task (i.e., where they had to classify briefly presented strings of letters as 'word' or 'non-word'). If the subject did not produce a definiendum, they were asked to rate their feeling of knowing (FOK) and then continued with the lexical decision task. The elapsed time between the rare-word association task and the lexical decisions task was interpreted as incubation (Yaniv and Meyer 1987). The results show that definitions that allowed for the retrieval of the correct definiendums or generated high FOKs produced priming (i.e., faster reaction times) in the lexical decision task.

According to the EII theory, a rare-word association trial produces a simultaneous search at the explicit and the implicit levels (Principle #2 of EII/CLARION). Because the target association is rare, explicit memory search is not likely to yield a satisfactory solution within the allotted time (i.e., the existing set of hard constraints does not necessarily lead to solutions). In contrast, implicit memory search is more likely to retrieve the desired association if given enough time, because soft constraint satisfaction can allow a partial match that can be iteratively improved. However, implicit memory search is often cut short by the experimenter who then asks the subject to take part in lexical decision trials (for the subjects who did not produce a definiendum). At the beginning of the lexical decision trials, implicit knowledge is still in the same state as it was at the end of the corresponding rare-word association trial. Hence, if the association was retrieved or nearly retrieved during the rare-word association trial (i.e., with high FOK), the memory search is not wasted and the target word is primed for the lexical decision trials. In contrast, the correct recognition of unrelated words (distractors) is not affected by the previous state of implicit knowledge in the lexical decision trials, because the cognitive work during the corresponding rare-word association trial was irrelevant. This conceptual explanation by EII led to a detailed computational model that produced simulation in line with Yaniv and Meyer's (1987) results. The results of 3,000 simulations with a CLARION-based model are shown in Figure 1.

4.2 Incubation in a Free Recall Task

Smith and Vela (1991) asked their subjects to recall as many words as possible from a study list in two separate free recall tests. The independent variables were the test durations and the elapsed time between the free recall tests (incubation). The dependent (outcome) variable was reminiscence (i.e., the number of new words recalled in the

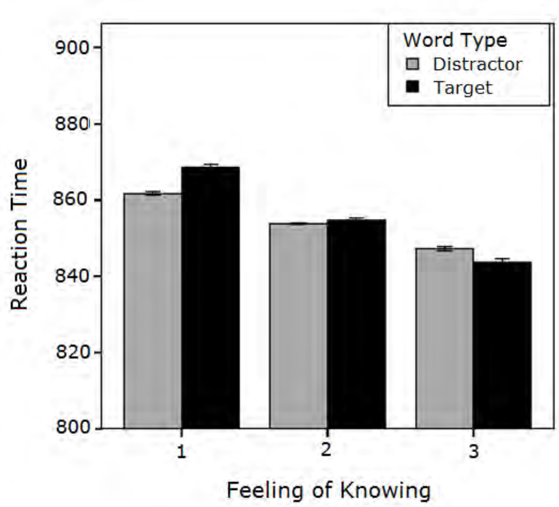


Figure 1: Simulated response times in the lexical decision task for subjects who did not produce a definiendum in the rare-word association task. From Helie and Sun (2010).

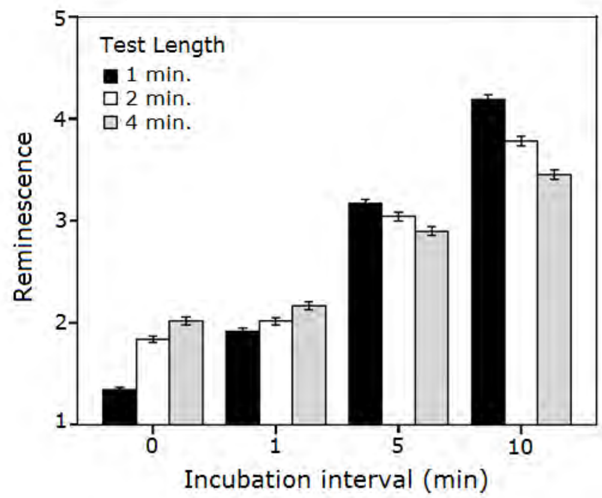


Figure 2: Simulated reminiscence effect. The black bars represent 1-minute tests, the white bars represent 2-minute tests, and the grey bars represent 4-minute tests. From Helie and Sun (2010).

second test that were not recalled during the first). The results show that incubation length increases reminiscence, but not test duration.

According to the EII theory, parallel memory searches are conducted in explicit and implicit memories during the free recall tests. However, the incubation period is different: Principle #1 of the EII theory (CLARION) stipulates that explicit memory search requires more attentional resources whereas implicit memory search is mostly automatic (i.e., it requires very little attentional resources). Thus, mostly implicit processes are deployed during the incubation phase, and words are retrieved from implicit memory (but not much from the explicit memory) during that period. These additional words are output at the beginning of the second test, increasing the number of words recalled in the second test (but not the first test). This conceptual explanation led a detailed model that produced simulations in line with Smith and Vela's (1991) results. The results of 12,000 CLARION-based simulations are shown in Figure 2.

4.3 Insight in Problem Solving

Durso, Rea, and Dayton (1994) asked human subjects to explain the following story:

> A man walks into a bar and asks for a glass of water. The bartender points a shotgun at the man. The man says 'thank you', and walks out.

The subjects' task was to explain why the sight of the shotgun replaced the man's need for a glass of water (i.e., because he had the hiccup). To explain this story, the subjects had two hours to ask the experimenter yes/no questions. When the time elapsed, each subject was classified as a 'solver' or as a 'non-solver' and its knowledge graph was drawn. Solvers and non-solvers knowledge graphs were shown to have different connectivity.

According to EII, reading the story results in both explicit memory retrieval and implicit memory search (incubation). However, explicit processing (mostly rule-based; Principle #1 of EII), brings up stereotypical semantic associations from the words included in the story. In contrast, the gradient of associations is flatter in implicit memory (Mednick 1962): the search is more diffused, and thus more remote ("creative") associations can be retrieved using soft constraint satisfaction. According to the EII theory, implicit processing allows the retrieval of more approximate, more hypothetical associations that differ from those retrieved explicitly. These implicit associations are then integrated with the result of explicit processing (Principle #4 of EII). If the chosen integrated association is deemed plausible (i.e., if the ICL is high enough), a question concerning the validity of this association is put to the experimenter. If the experimenter confirms the association, it is added into explicit knowledge; otherwise, it is removed. This process is iterated, with explicit and implicit processing reinitiated with the new state of the knowledge. This iterative process ends when the subject finds the correct solution or the allowed time elapses. The results of 8,000 CLARION-based simulations show that, consistent with this EII explanation, the probability of solving the problem increases with the amount of noise in the implicit association retrieval (see Helie and Sun 2010 for details).

4.4 Overshadowing in Problem Solving

Schooler, Ohlsson, and Brooks (1993) asked subjects to solve the following problem:

> A dealer of antique coins got an offer to buy a beautiful bronze coin. The coin had an emperor's head on one side and the date 544 B.C. stamped on the other. The dealer examined the coin, but instead of buying it, he called the police. Why?

Each subject had two minutes to solve this problem. Following this initial problem-solving period, half of the subjects were assigned to an unrelated task while the remaining half were asked to verbalize their problem solving strategies. In both cases, the interruption period lasted 90 seconds and was followed by another four-minute attempt to solve the initial problem. The dependant variable was the proportion of insight problems solved by the subjects. The results show that an overly explicit mode of problem solving (verbalization) reduces the probability of solving insight problems.

According to the EII theory, both explicit and implicit processing are initiated by the problem (Principle #2 of EII). However, insight problems are more likely to be solved by the implicit processes, because rule-based processes are ineffective in solving such problems (Bowden et al. 2005). In line with the earlier explanation of Durso et al.'s (1994) experiment, implicit hypotheses are generated using implicit knowledge and then verified using explicit knowledge. When the subjects were interrupted to take part in an unrelated activity, hypotheses were still being generated implicitly [similar to the explanation of Smith and Vela's (1991) reminiscence data]. In contrast, subjects who had to verbalize their problem solving strategies could not generate implicit hypotheses easily (because they were likely stuck in an explicit processing mode). When the subjects went back to working on the problem, the verbalization group had fallen behind, so the overall probability of solving the problem by the verbalization group was lower than that of the control group. The results of 10,000 CLARION-based simulations are shown in Figure 3.

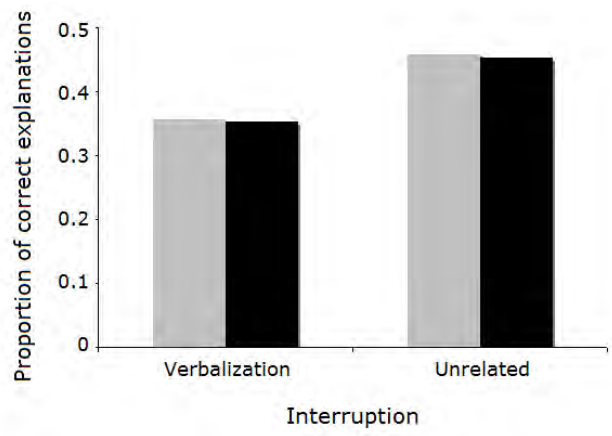


Figure 3: Proportion of correct explanations selected by the subjects in Schooler et al.'s (1993) Experiment 1 (gray bars) and by the CLARION simulations (black bars). The *x*-axis represents the distracting activity during the interruption period. From Helie and Sun (2010).

5. Conclusion

This work shows how a psychologically realistic cognitive architecture (e.g., CLARION; Sun 2002, Sun et al. 2001, 2005) can be used to derive an integrative theory of creative problem solving (e.g., EII; Helie and Sun 2010). Cognitive architectures generally integrate many components in order to produce intelligent behavior. In EII, the key components were explicit and implicit processing. By incorporating both explicit and implicit processes, the proposed EII theory is able to provide a unified framework for re-interpreting and integrating some important (but fragmentary) theories of incubation, insight, and creativity (see Helie and Sun 2010 for details of re-interpretation and integration). The EII theory is obviously not complete. It needs to move on to account for real-world cases of creative problem solving. However, it is more complete and more integrated than previous theories.

In relation to AI, a unified computational model (based on CLARION) was developed to simulate empirical data in widely differing psychological experiments (e.g., free recall, lexical decision, problem solving). The computational model used different types of neural networks to simulate explicit processing (with localist, feedforward networks) and implicit processing (with distributed, fully recurrent, attractor networks). Synergistically integrating the output of these components was essential in capturing the psychological data. Cognitive architectures are a useful way of exploring the advantage of synergistically combining several (sometimes specialized) computational models, because no single AI model can account for human intelligence by itself. Future work should be devoted to the integration of more modules within CLARION, and to tackle more complex real-world creative problem solving situations.

Acknowledgments

Preparation of this manuscript was supported by research grants DASW01-00-K-0012 and W74V8H-04-K-0002 provided by the *Army Research Institute*, and N00014-08-1-0068 provided by the *Office of Naval Research* to the second author.

References

Bowden, E.M., Jung-Beeman, M., Fleck, J., and Kounios, J. 2005. New Approaches to Demystifying Insight. *Trends in Cognitive Science* 9: 322-328.

Bowers, K.S., Regehr, G., Balthazard, C., and Parker, K. 1990. Intuition in the Context of Discovery. *Cognitive Psychology* 22: 72-110.

Costermans, J., Lories, G., and Ansay, C. 1992. Confidence Level and Feeling of Knowing in Question Answering: The Weight of Inferential Processes. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 18: 142–150.

Duch, W. 2006. Computational Creativity. In *Proceedings of the International Joint Conference on Neural Networks*, 435-442. Vancouver, BC: IEEE Press.

Durso, F.T., Rea, C.B., and Dayton, T. 1994. Graph-theoretic Confirmation of Restructuring During Insight. *Psychological Science* 5: 94-98.

Evans, J.B.T. 2006. The Heuristic-analytic Theory of Reasoning: Extension and Evaluation. *Psychonomic Bulletin & Review* 13: 378-395.

Helie, S., and Sun, R. 2010. Incubation, Insight, and Creative Problem Solving: A Unified Theory and a Connectionist Model. *Psychological Review* 117: 994-1024.

Helie, S., Proulx, R., and Lefebvre, B. 2011. Bottom-up Learning of Explicit Knowledge using a Bayesian Algorithm and a New Hebbian Learning Rule. *Neural Networks* 24: 219-232.

Johnson, T.R., and Krems, J.F. 2001. Use of Current Explanations in Multicausal Abductive Reasoning. *Cognitive Science* 25: 903-939.

Langley, P., Laird, J.E., and Rogers, S. 2009. Cognitive Architectures: Research Issues and Challenges. *Cognitive Systems Research* 10:141-160.

Lubart, T.I. 2001. Models of the Creative Process: Past, Present and Future. *Creativity Research Journal* 13: 295-308.

Mednick, S.A. 1962. The Associative Basis of the Creative Process. *Psychological Review* 69: 220-232.

Pols, A.J.K. 2002. Insight Problem Solving. Ph.D. diss, Department of Psychology, University of Utrecht, Netherlands.

Rips, L.J. 1994. *The Psychology of Proof: Deductive Reasoning in Human Thinking*. Cambridge, MA: MIT Press.

Schooler, J.W., Ohlsson, S., and Brooks, K. 1993. Thoughts Beyond Words: When Language Overshadows Insight. *Journal of Experimental Psychology: General* 122: 166-183.

Smith, S.M., and Dodds, R.A. 1999. Incubation. In M.A. Runco & S.R. Pritzker (Eds.) *Encyclopedia of Creativity* (pp. 39-43). San Diego, CA: Academic.

Smith, S.M., and Vela, E. 1991. Incubated Reminiscence Effects. *Memory & Cognition* 19: 168-176.

Sun, R. 1995. Robust Reasoning: Integrating Rule-based and Similarity-based Reasoning. *Artificial Intelligence* 75: 241-296.

Sun, R. 2002. *Duality of the Mind*. Mahwah, NJ: Lawrence Erlbaum Associates.

Sun, R. 2004. Desiderata for Cognitive Architectures. *Philosophical Psychology* 17: 341-373.

Sun, R., Merrill, E., and Peterson, T. 2001. From Implicit Skills to Explicit Knowledge: A Bottom-up Model of Skill Learning. *Cognitive Science* 25: 203-244.

Sun, R., Slusarz, P., and Terry, C. 2005. The Interaction of the Explicit and the Implicit in Skill Learning: A Dual-process Approach. *Psychological Review* 112: 159-192.

Wallas, G. 1926. *The Art of Thought*. New York: Franklin Watts.

Yaniv, I., and Meyer, D.E. 1987. Activation and Metacognition of Inaccessible Stored Information: Potential Bases for Incubation Effects in Problem Solving. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 13: 187-205.

Paper

Why Have We Passed "Neural Networks Do Not Abstract Well"?

Juyang Weng*

Michigan State University, USA

**corresponding author*: weng@cse.msu.edu

Abstract

It has been argued that prior artificial networks do not abstract well. A Finite Automaton (FA) is a base net for many sophisticated probability-based systems of artificial intelligence, for state-based abstraction. However, an FA processes symbols, instead of images that the brain senses and produces (e.g., sensory images and effector images). This paper informally introduces recent advances along the line of a new type of, brain-anatomy inspired, neural networks —Developmental Networks (DNs). The new theoretical results discussed here include: (1) From any complex FA that demonstrates human knowledge through its sequence of the symbolic inputs-outputs, the Developmental Program (DP) of DN incrementally develops a corresponding DN through the image codes of the symbolic inputs-outputs of the FA. The DN learning from the FA is incremental, immediate and errorfree. (2) After learning the FA, if the DN freezes its learning but runs, it generalizes optimally for infinitely many image inputs and actions based on the embedded inner-product distance, state equivalence, and the principle of maximum likelihood. (3) After learning the FA, if the DN continues to learn and run, it "thinks" optimally in the sense of maximum likelihood based on its past experience. These three theoretical results have also been supported by experimental results using real images and text of natural languages. Together, they seem to argue that the neural networks as a class of methods has passed "neural networks do not abstract well".

1. Introduction

Studies on artificial neural networks (ANN) in the 1970's and 1980's (e.g., Fukushima 1975 [7], Grossberg 1975 [11], Hopfield 1982 [14], Rumelhart, McClelland & others 1986 [35], [27]) have been supported by a series of documented advantages of neural networks, including (1) non-algorithmic in task space, (2) uniform processors suited for massively parallel hardware, (3) fault tolerance, (4) numerical in signal space, and (5) feedforward networks are universal approximators of a certain class of static, multivariate functions [8], [15], [2]. ANNs have been also been identified by their network style of computation, called connectionist approaches.

Marvin Minsky 1991 [28] and others argued that symbolic models are logic and neat, but connectionist models are analogical and scruffy. Such criticisms have different ways of characterization, but we can use a simple sentence "neural networks do not abstract well." Clearly, a lot of new work has been done for neural network since then (e.g., see a recent review [46]). However, this image of ANN has not fundamentally changed in the larger research community of intelligence modeling, natural intelligence and artificial intelligence. For example, at the David Rumelhart Memorial talk August 3, 2011 during the International Joint Conference on Neural Networks, Michael I. Jordan started with a statement that neural networks do not abstract well and he will talk about symbolic methods today. Jordan did some work on neural networks in the 1980s [19].

The term "connectionist" is misleading in distinguishing symbolic models and ANNs, since a probability based symbolic model is also a network whose representation is also distributed. Weng 2011 [46] proposed two classes, symbolic models and emergent models. By definition [46], an *emergent representation* emerges autonomously from system's interactions with the *external* (outside the skull) world and the *internal world* (inside the skull) via the brain's sensors and effectors without using the handcrafted (or gene-specified) content or the handcrafted boundaries for concepts about the extra-body concepts.

Many basic models of ANNs (e.g., Self-Organization Maps (SOM), feed-forward networks with gradient-based learning) use emergent representations but symbolic models use task-specific, handcrafted representations. A hybrid model, partially emergent and partially handcrafted, still belongs to the category of symbolic model. The brain seems to use emergent representations which emerge autonomously from learning experience, regulated by the genome in the nucleus of every cell (e.g., see Purve et al. 2004 [33] and Sur & Rubenstein 2005 [37]). All cells, other than the original zygote, in the body of a multi-cellular eukaryotic life are emergent from the zygote, whose emergence is regulated by the genome in the nucleus of every cell.

It seems to be the emergence of such network represent-tation – the process of autonomous development – that makes it hard to address the criticism "neural networks do not abstract well". However, autonomous emergence of brain's internal representation seems also the essential process for an animal brain to do what it does well as we know it.

In this article, I introduce a recent theory that maps a class of brain-inspired networks – Developmental Networks

(DNs) to any Finite Automaton (FA), a "common-denominator" model of all practical Symbolic Networks (SNs). From this FA, we can see what is meant by "abstraction". This mapping explains why such a new class of neural networks abstract at least as well as the corresponding SNs. This seems to indicate that our humans, collectively, have passed "neural networks do not abstract well."

The additional properties discussed in this paper include: (1) In contrast with an SN where the meanings of each node are *hand-selected* and boundaries between conceptual modules are *handcrafted*, there is a class of Generative DNs (GDNs) whose learning is fully *autonomous* inside each network, using the signals in the sensors and effectors. (2) In contrast with an SN whose expansion requires a manual re-design by the original human designer, the expansion (growth) of a GDN is fully autonomous inside the network, through observing an FA which collectively represents the human society's consistent knowledge. Such learning by the DN from the FA is incremental, immediate, and error-free. (3) The input symbols and output symbols of an FA are static, but the representations of input vectors and output vectors of a GDN are emergent from the natural environment (e.g., natural images, and natural arm motions). (4) The consideration of performance requires optimality for both types of models, symbolic (e.g., Markov models based on FA) and emergent (i.e., GDN). While the probability version of FA is limited by the static design of the input symbol set and the output symbol set, the outputs from the GDN at any time are optimal in the sense of maximum likelihood (ML), conditioned on the limited number of internal nodes and the limited amount and quality of the learning experience so far.

2. Two Types of Models

In this section, we discuss two types of models, symbolic and emergent.

2.1. Symbolic networks

Given a task, a human designer in Artificial Intelligence (AI) [21], [10] or Cognitive Science [1], [39] handcrafts a Symbolic Network (SN), using handpicked task-specific concepts as symbols. The "common denominator" network underlying many such SNs is the Finite Automaton (FA) whose probabilistic extensions include the Hidden Markov Model (HMM), the Partially Observable Markov Decision Processes (POMDP) and the Bayesian Nets (also called belief nets, semantic nets, and graphical models).

Such an FA is powerful by recursively directing many different sensory sequences (e.g., "kitten" and "young cat") into the same equivalent state (e.g., z_3) and its future processing is always based on such an equivalence. For example, state z_4 means that the last meaning of all input subsequences that end at z_4 is "kitten looks" or equivalent. However, the resulting machine does not truly understand the symbolic concepts and is unable to learn new concepts beyond possible re-combinations of handpicked symbols.

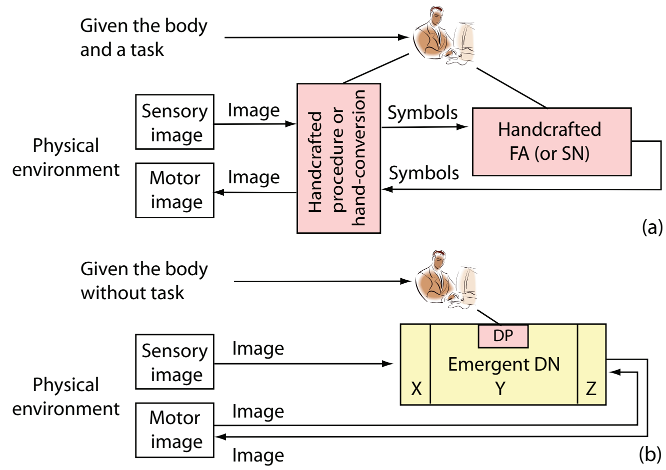


Figure 1. Comparison between a symbolic FA (or SN) and an emergent DN. (a) Given a task, an FA (or SN), symbolic, handcrafted by the human programmer using a static symbol set. (b) A DN, which incrementally learns the FA but takes sensory images directly and produces effector images directly. Without given any task, a human designs the general-purpose Developmental Program (DP) which resides in the DN as a functional equivalent of the "genome" that regulates the development — fully autonomous inside the DN.

2.2. Emergent networks

The term "connectionist" has been misleading, diverting attention to only network styles of computation that do not address how the internal representations emerge without human programmer's knowledge about tasks. Furthermore, the term "connectionist" has *not* been very effective to distinguish (emergent) brain-like networks from SNs. For example, Jordan & Bishop [18] used neural networks to name SNs, and Tenenbaum et al. [40] used SNs to model the mind.

An emergent representation emerges autonomously from system's interactions with the *external* world (outside the brain or network) and the *internal world* via its sensors and its effectors without using the handcrafted (or gene-specified) content or the handcrafted boundaries for concepts about the extra-body environments.

Feed-forward [36], [34] and recurrent [12], [49] networks, use images (numeric patterns) as representations. Recurrent networks can run continuously to take into account temporal information. The network representations are emergent in the sense that the internal representations, such as network connection patterns, multiple synaptic weights, and neuronal responses, emerge automatically through the interactions between the learner system and its environment. However, it is unclear how a recurrent network can model a brain.

Vincent Müller [30] stated: "How does physics give rise to meaning? We do not even know how to start on the hard problem." This question is indeed challenging to answer since the internal representations inside the brain skull do not permit handcrafting. This paper explains that this hard problem now has a solution — DN. The internal representations of a DN emerge from a single cell (zygote) through experience, regulated by the Developmental Program (DP). An artificial DP is handcrafted by a human, to short cut extremely expensive evolution.

2.3. *Innate problem-specific structure?*

Neuroanatomical studies, surveyed by Felleman & Van Essen as early as 1991 [5] reported that in the brain the motor areas feed its signals back to the earlier sensory areas and, furthermore, in general, almost every area in the brain feeds its signals to multiple earlier areas. Are such areas problem-specfiic?

Computationally, feed-forward connections serve to feed sensory features [31], [38] to motor area for generating behaviors. It has been reported that feed-backward connections can serve as class supervision [12], attention [3], [4], and storage of time information [49]. What developmental mechanisms enable the brain to establish feed-backward connections, as well as feed-forward connections? Are such developmental mechanisms problem-specific?

Gallistel reviewed [9]: "This problem-specific structure, they argue, is what makes learning possible." "Noam Chomsky ... , Rochel Gelman, Elizabeth Spelke, Susan Carey, and Renee Baillargeon have extended this argument."

However, the theory introduced hear seems to show that the brain does not have to work in such a problem specific way if we analyze how a Generative DN (GDN) dynamically establishes connections, using the automata theory developed for modeling computer-like reasoning. The Developmental Network (DN) here provides an example — a problem-specific (or task-specific) structure is unnecessary for DN learning.

3. Symbolic Networks

The brain's spatial network seems to deal with general temporal context without any explicit component dedicated to time as argued by [26], [20], but its mechanisms are still largely elusive.

3.1. *Finite automata*

FA is amenable to understanding the brain's way of temporal processing. An FA example is shown in Fig. 2(a). At each time instance, the FA is at a state. At the beginning, our example is at state z_1. Each time, it receives a label as input (e.g., "young"). Depending on its current state and the next input, it transits to another state. For example, if it is at z_1 and receives label "young", it transits to "z_2", meaning "I got 'young'." All other inputs from z_1 leads back to z_1 meaning "start over". The states have the following meanings: z_1: start; z_2: "young"; z_3: "kitten" or equivalent; z_4: "kitten looks" or equivalent. An FA can abstract. For example, our FA example treats "young cat" and "kitten" the same in its state output.

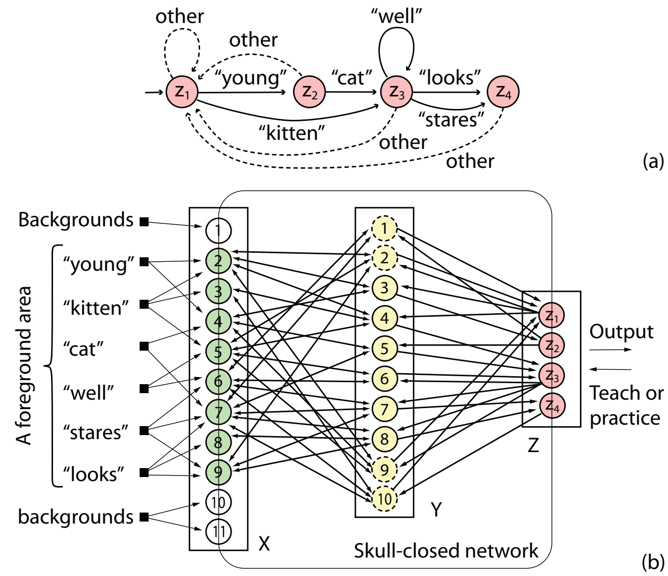


Figure 2. Conceptual correspondence between an Finite Automaton (FA) with the corresponding DN. (a) An FA, handcrafted and static. (b) A corresponding DN that simulates the FA. It was taught to produce the same input-out relations as the FA in (a). A symbol (e.g., z_2) in (a) corresponds to an image (e.g., $(z_1, z_2, ..., z_4) = (0, 1, 0, 0)$) in (b).

A finite automaton (FA) has been defined as a language acceptor in the traditional automata theory [13]. To model an agent, it is desirable to extend the definition of the FA as a language acceptor to an agent FA. An agent FA (AFA) M for a finite symbolic world is the same as a language acceptor FA, except that it outputs its current state, instead of an action (accept or not accept), associated with the state. In the following, an FA means an AFA by default.

The input space is denoted as $\Sigma = \{\sigma_1, \sigma_2, ..., \sigma_l\}$, where each σ_i representing an input symbol, whose meaning is only in the design document, not something that the FA is aware of. The set of states can be denoted as $Q = \{q_1, q_2, ..., q_n\}$. Like input symbols, the meanings of state q_i is also in the design document, but the FA is not "aware" the meanings. Fig. 2(a) gives a simple example of FA.

3.2. *Completeness of FA*

Let Σ^* denote the set of all possible strings of any finite $n \geq 0$ number of symbols from Σ. All possible input sequences that lead to the same state q are equivalent as far as the FA is concerned. It has been proved that an FA with n states partitions all the strings in Σ^* into n sets. Each set is called equivalence class, consisting of strings that are equivalent. Since these strings are equivalent, any string x in the same set can be used to denote the equivalent class, denoted as $[x]$. Let Λ denote an empty string. Consider the example in Fig. 2(a). The FA partitions all possible strings into 4 equivalent classes. All the strings in the equivalent class $[\Lambda]$ end in z_1. All strings in the equivalent class ["kitten" "looks"] end in z_4, etc.

The completeness of agent FA can be described as follows. When the number of states is sufficiently large, a properly designed FA can sufficiently characterize the cognition and behaviors of an agent living in the symbolic world of vocabulary Σ.

3.3. Other types of automata

Furthermore, there are four types of well-known automata, FA, Pushdown Automata, Linear Bounded Automata (LBA), and Turing machines.

Automata have been used to model the syntax of a language, which does not give much information about semantics. As argued by linguisticists [41], [16], semantics is primary in language acquisition, understanding and production, while syntax is secondary.

The DN theory below enables the semantics to emerge implicitly in its connection weights in the network. In particular, it treats syntax as part of the emergent semantics. It does not separately treat syntax as the above three types of automata. Therefore, FA is sufficient for a state-based symbolic agent.

3.4. Symbolic networks: Probabilistic variants

FA has many probabilistic variants (PVs), e.g., HMM, POMDP, and Bayesian Nets. Like FA, each node (or module) of a PV is defined by the handcrafted meaning which determines what data humans feed it during training. A PV can take vector inputs (e.g., images) based on handcrafted features (e.g., Gabor filters). The PV determines a typically better boundary between two ambiguous symbolic nodes (or modules) using probability estimates, e.g., better than the straight nearest neighbor rule. However, this better boundary does not change the symbolic nature of each node (or module). Therefore, FA and all its PVs are all called Symbolic Networks (SNs) here.

3.5. Power of SN

The major power of SN lies in the fact that it partitions infinitely many input sequences into a finite number of states. Each state lumps infinitely many possible state trajectories (e.g., "kitten" and "young cat") into the same single state (z_3). For example, state z_4 means that the last meaning of all input subsequences that end at z_4 is "kitten looks" or equivalent. Regardless what the previous trajectories were before reaching the current state, as long as they end at the same state now they are treated exactly the same in the future. This enables the SN to generalize (act correctly) for infinitely many state trajectories that it has not been observed. For example, in Fig. 2(a), as long as "kitten" has been taught to reach z_3, "kitten looks", "kitten stares", "kitten well looks" so on all lead to z_4, although these strings have never been observed.

3.6. Limitations of SN

In fact, an SN relies on humans to abstract from real world non-symbolic data, from sensors such as images, sounds, and effectors such as motor control signals. Therefore, the power of abstraction does not lie in FA, but in a human designer. An SN has the following major limitations:

(1) An SN is intractable for dealing with input symbols for real physical world. The human designer needs to handcraft Σ — sensory abstraction — to well represent all possible inputs to an acceptable precision. The number of inputs is intractably too large and handcrafting Σ is complex. If each input involves c concepts and each concept has v possible values, the potential number of input symbols is v^c, exponential in c. Suppose that we have $c = 22$ concepts and each concept has v=4 values (e.g., unknown, low, high, do-not-care), the number of possible input symbols is $v^c = 4^{22} = 16^{11}$, larger than the number of neurons in the brain. Here is an example of 23 extra-body concepts: name, type, horizontal location, vertical location, apparent scale, size, pitch orientation, yaw orientation, weight, material, electrical conductivity, shape, color, surface texture, surface reflectance, deformability, fragility, purpose, having life, edibility, usage, price, and owner.

(2) Likewise, an SN is intractable for dealing with output (state) symbols for real physical world. The human designer must handcraft Q — state abstraction — to well represent all possible output states to an acceptable precision. It is intractable for a human to examine many symbolic states for a large problem and decide which ones are equivalent and should be merged as a single Meta symbolic state. Therefore, a human designs conditions for every Meta state without exhaustively checking its validity. This is a complexity reason why symbolic agents are brittle.

(3) The base network FA of SN is static. It does not have emergent representations like those in the brain. Therefore, it cannot think like the brain for new concepts. For example, it cannot be creative, going beyond a finite number of combinations of these handcrafted static concepts.

4. Developmental Networks

Weng 2010 [43] discussed that a DN can simulate any FA.

4.1. DN architecture

A basic DN, has three areas, the sensory area X, the internal (brain) area Y and the motor area Z. An example of DN is shown in Fig. 2(b). The internal neurons in Y have bi-directional connection with both X and Z.

The DP for DNs is task-specific as suggested for the brain in [47] (e.g., not concept-specific or problem specific). In contrast to a static FA, the motor area Z of a DN can be directly observed by the environment (e.g., by the teacher) and thus can be calibrated through interactive teaching from the environment. The environmental concepts are learned incrementally through interactions with the environments.

For example, in Fig. 2(b), the "young" object makes the pixels 2 and 4 bright and all other green pixels dark. However, such an image from the "young" object is not known during the programming time for the DP.

In principle, the X area can model any sensory modality (e.g., vision, audition, and touch). The motor area Z serves both input and output. When the environment supervises Z, Z is the input to the network. Otherwise, Z gives an output vector to drive effectors (muscles) which act on the real world. The order of areas from low to high is: X, Y, Z. For example, X provides bottom-up input to Y, but Z gives top-down input to Y.

4.2. DN algorithm

DN is modeled as an area of the brain. It has its area Y as a "bridge" for its two banks, X and Z. If Y is meant for modeling the entire brain, X consists of all receptors and Z consists of all muscle neurons. Y potentially can also model any Brodmann area in the brain. According to many studies in detailed review by Felleman & Van Essen [5], each area Y connects in bi-directionally with many other areas as its two extensive banks.

The most basic function of an area Y seems to be prediction — predict the signals in its two vast banks X and Y through space and time. The prediction applies when part of a bank is not supervised. The prediction also makes its bank less noisy if the bank can generate its own signals (e.g., X).

A secondary function of Y is to develop bias (like or dislike) to the signals in the two banks, through what is known in neuroscience as neuromodulatory systems.

Although being convenient for studying infinitesimal changes (see, e.g., [17]), a continuous time model seems not very effective to explain network abstraction. Such a weakness is especially obvious for multiple neurons and brain-scale networks. I use a discrete time formulation, which is exact regardless how fast the network is temporally sampled (updated). Let the network update time interval be δ. The smaller the δ, the smaller the latency between a stimulus and the responsive action. The human brain seems to have a latency on the order of 100ms. In the following, δ is consider a unit, so we denote the time by integers $t = 0, 1, 2, ...$

The DN algorithm is as follows. Input areas: X and Z. Output areas: X and Z. The dimension and representation of X and Y areas are hand designed based on the sensors and effectors of the robotic agent or biologically regulated by the genome. Y is skull-closed inside the brain, not directly accessible by the external world after the birth.

1) At time $t = 0$, for each area A in $\{X, Y, Z\}$, initialize its adaptive part $N = (V, G)$ and the response vector $\mathbf{r}$, where V contains all the synaptic weight vectors and G stores all the neuronal ages. For example, use the generative DN method discussed below.

2) At time $t = 1, 2, ...$, for each A in $\{X, Y, Z\}$ repeat:
   a) Every area A performs mitosis-equivalent if it is needed, and initialize the weight vector if the new neuron using its bottom-up and top-down inputs $\mathbf{b}$ and $\mathbf{t}$, respectively.
   b) Every area A computes its area function f, described below,
   $$(\mathbf{r}', N') = f(\mathbf{b}, \mathbf{t}, N)$$
   where $\mathbf{r}'$ is its response vector.
   c) For every area A in $\{X, Y, Z\}$, A replaces: $N \leftarrow N'$ and $\mathbf{r} \leftarrow \mathbf{r}'$.

In the remaining discussion, we assume that Y models the entire brain. If X is a sensory area, $\mathbf{x} \in X$ is always supervised. The $\mathbf{z} \in Z$ is supervised only when the teacher chooses to. Otherwise, $\mathbf{z}$ gives (predicts) effector output.

Put intuitively, like the brain, the DN repeatedly predicts the output Z for the next moment. When the predicted Z is mismatched, learning proceeds to learn the new information from Z. But, there is no need to check mismatches: learning takes place anyway.

A generative DN (GDN) automatically generates neurons in the Y area. If $(\mathbf{b}, \mathbf{t})$ is observed for the first time (the pre-response of the top-winner is not 1) by the area Y, Y adds (e.g., equivalent to mitosis and cell death, spine growth and death, and neuronal recruitment) a Y neuron whose synaptic weight vector is $(\mathbf{b}, \mathbf{t})$ with its neuronal age initialized to 1. The idea of adding neurons is similar to ART and Growing Neural Gas but they do not take action as input and are not state-based.

4.3. Unified DN area function

It is desirable that each brain area uses the same area function f, which can develop area specific representation and generate area specific responses. Each area A has a weight vector $\mathbf{v} = (\mathbf{v}_b, \mathbf{v}_t)$. Its pre-response value is:

$$r(\mathbf{v}_b, \mathbf{b}, \mathbf{v}_t, \mathbf{t}) = \dot{\mathbf{v}} \cdot \dot{\mathbf{p}} \tag{1}$$

where $\dot{\mathbf{v}}$ is the unit vector of the normalized synaptic vector $\mathbf{v} = (\dot{\mathbf{v}}_b, \dot{\mathbf{v}}_t)$, and $\dot{\mathbf{p}}$ is the unit vector of the normalized input vector $\mathbf{p} = (\dot{\mathbf{b}}, \dot{\mathbf{t}})$. The inner product measures the degree of match between these two directions $\dot{\mathbf{v}}$ and $\dot{\mathbf{p}}$, because $r(\mathbf{v}_b, \mathbf{b}, \mathbf{v}_t, \mathbf{t}) = \cos(\theta)$ where θ is the angle between two unit vectors $\dot{\mathbf{v}}$ and $\dot{\mathbf{p}}$. This enables a match between two vectors of different magnitudes (e.g., a weight vector from an object viewed indoor to match the same object when it is viewed outdoor). The pre-response value ranges in $[-1, 1]$.

This pre-response is inspired by how each neuron takes many lines of input from bottom-up and top-down sources. It generalizes across contrast (i.e., the length of vectors). It uses inner-product $\dot{\mathbf{v}} \cdot \dot{\mathbf{p}}$ to generalize across many different vectors that are otherwise simply different as with symbols in an FA. The normalization of the bottom-up part and the top-down part separately is for both the bottom-up source and top-down source to be taken into account, regardless the dimension and magnitude of each source.

To simulate lateral inhibitions (winner-take-all) within each area A, top k winners fire. Considering $k = 1$, the winner neuron j is identified by:

$$j = \arg \max_{1 \le i \le c} r(\mathbf{v}_{bi}, \mathbf{b}, \mathbf{v}_{ti}, \mathbf{t}). \tag{2}$$

The area dynamically scale top-k winners so that the top-k respond with values in $(0, 1]$. For $k = 1$, only the single winner fires with response value $y_j = 1$ (a pike) and all other neurons in A do not fire. The response value y_j approximates the probability for $\dot{\mathbf{p}}$ to fall into the Voronoi region of its $\dot{\mathbf{v}}_j$ where the "nearness" is $r(\mathbf{v}_b, \mathbf{b}, \mathbf{v}_t, \mathbf{t})$.

4.4. DN learning: Hebbian

All the connections in a DN are learned incrementally based on Hebbian learning — cofiring of the pre-synaptic activity $\dot{\mathbf{p}}$ and the post-synaptic activity y of the firing neuron. If the pre-synaptic end and the post-synaptic end fire together, the synaptic vector of the neuron has a synapse gain $y\dot{p}$. Other non-firing neurons do not modify their memory. When a neuron j fires, its firing age is incremented $n_j \leftarrow n_j + 1$ and then its synapse vector is updated by a Hebbian-like mechanism:

$$\mathbf{v}_j \leftarrow w_1(n_j)\mathbf{v}_j + w_2(n_j) y_j \dot{\mathbf{p}} \tag{3}$$

where $w_2(n_j)$ is the learning rate depending on the firing age (counts) n_j of the neuron j and $w_1(n_j)$ is the retention rate with $w_1(n_j) + w_2(n_j) \equiv 1$. The simplest version of $w_2(n_j)$ is $w_2(n_j) = 1/n_j$ which corresponds to:

$$\mathbf{v}_j^{(i)} = \frac{i-1}{i}\mathbf{v}_j^{(i-1)} + \frac{1}{i} 1 \dot{\mathbf{p}}(t_i), i = 1, 2, ..., n_j,$$

where t_i is the firing time of the post-synaptic neuron j. The above is the recursive way of computing the batch average:

$$\mathbf{v}_j^{(n_j)} = \frac{1}{n_j} \sum_{i=1}^{n_j} \dot{\mathbf{p}}(t_i)$$

where is important for the proof of the optimality of DN in Weng 2011 [44].

The initial condition is as follows. The smallest n_j in Eq. (3) is 1 since $n_j = 0$ after initialization. When $n_j = 1$, $\mathbf{v}_j$ on the right side is used for pre-response competition but does not affect $\mathbf{v}_j$ on the left side since $w_1(1) = 1 - 1 = 0$.

A component in the gain vector $y_j \dot{\mathbf{p}}$ is zero if the corresponding component in $\dot{\mathbf{p}}$ is zero. Each component in $\mathbf{v}_j$ so incrementally computed is the estimated probability for the pre-synaptic neuron to fire under the condition that the post-synaptic neuron fires.

4.5. GDN area functions

For simplicity, let us consider $k = 1$ for top-k competition.

Algorithm 1 (Y area function):
1) Every neuron computes pre-response using Eq. (1).
2) Find the winner neuron j using Eq. (2).
3) If the winner pre-response is less than 0.9999, generate a Y neuron using the input $\dot{\mathbf{p}}$ as the initial weight with age 0. The new Y neuron is the winner for sure.
4) The winner neuron j increments its age: $n_j \leftarrow n_j + 1$, fires with $y_j = 1$, and updates its synaptic vector, using Eq. (3).
5) All other neurons do not fire, $y_i = 0$, for all $i \neq j$, and do not advance their ages.

Algorithm 2 (Z Area function): This version has $k = 1$ for top-k competition within each concept zone.

1) If the dimension of Y has not been incremented, do:
   a) Every neuron computes pre-response using Eq. (1).
   b) Find the winner neuron j using Eq. (2).

   Otherwise, do the following:
   a) Supervise the pre-response of every neuron to be 1 or 0 as desired.
   b) Add a dimension for the weight vector of every neuron, initialized to be 0, which may be immediately updated below.
2) Each winner or supervised-to-fire neuron j increment its age: $n_j \leftarrow n_j + 1$, fire with $z_j = 1$, and updates its synaptic vector, using Eq. (3).
3) All other neurons do not fire, $z_i = 0$, for all $i \neq j$, and do not advance their ages.

The Y area function and the Z functions are basically the same. Z can be supervised but Y cannot since it is inside the closed "skull". During the simple mode of learning discussed here, neurons responding for backgrounds are suppressed (not attending), so that no neurons learn the background.

5. DN Abstraction

As one can expect, a handcrafted FA does not have any problem of convergence as it is statically handcrafted. However, how well can a DN abstract? Weng 2011 [45] provided the following three theorems, which provide properties about how well a DN can abstract, using FA as a basis. The proofs for the three theorems are available as a report [44], currently under review by a journal.

Since this paper is meant for a general reader of the INNS society journal, let us have an informal explanation of the three theorems and their importance.

5.1. GDN learns any FA immediately and error-free

Since FA is a "common denominator" model of many symbolic models (e.g., HMM, POMDP, Bayesian nets, semantic nets, belief nets, and graphical models), it is desirable to show that neural networks can incrementally learn any FA by autonomously organizing its emergent internal representations.

Frasconi et al. 1995 [6] programmed (not through learning) a feed-forward network to explicitly compute a statically given (as a batch) state transition of a fully given FA. They require a special coding of each state so that the Hamming distance is 1 between any source state and any target state. This means that transition to the same state (a loop) is impossible. If such a loop is necessary, they added a transition state to satisfy the requirement for unit Hamming distance. Omlin & Giles 1996 [32] programed (not through learning) a second-order network for computing a statically given (as a batch) state transition of an FA. By 2nd order, the neuronal input contains the sum of weighted multiplications (hence the 2nd order), between individual state nodes and individual input nodes.

The Theorem 1 in Weng 2011 [45], [44] established that goal above has been not only reached, but also two somewhat surprising properties — immediate and error-free. The text version of the Theorem 1 us as follows.

The general-purpose DP can incrementally grow a GDN to simulate any given FA on the fly, so that the performance of the DP is immediate and error-free, provided that the Z area of the DN is supervised when the DN observes each new state transition from the FA. The learning for each state transition completes within two network updates. There is no need for a second supervision for the same state transition to reach error-free future performance. The number of Y neurons in the DN is the number of state transitions in the FA. However, the DN generalizes with 0% action error for infinitely many equivalent input sequences that it has not observed from the FA but are intended by the human FA designer.

The GDN simulates each new state transition of FA by creating a new Y neuron that immediately initializes with the image code of the state $q(t-1)$ and the image code of the input $\sigma(t-1)$ through the first network update (see the Y area at time $t-0.5$). During the next network update, the Z area is supervised as the image code of the desired state $q(t)$ and the links from the uniquely firing new Y neuron to the firing Z neurons are created through a Hebbian mechanism. Since the match of the new Y neuron is exact and only one Y neuron fires at any time, the Z output is always error-free if all image codes for Z are known to be binary (spikes).

Let us discuss the meaning of this theorem. Suppose that the FA is collectively acquired by a human society, as a static ontology (common sense knowledge and specialty knowledge). Each input image $\mathbf{x}(t) \in X$ is a view of attended object (e.g., a cat). Then this FA serves as a society intelligence demonstrator representing many human teachers whom an agent meets incrementally from childhood to adulthood. A different FA represents a different career path. Then, a DN can learn such symbolic knowledge of the FA immediately, incrementally, and error-free. This is not what any prior neural network can do. Conventional networks require many iterative approximations that may lead to local minima.

Furthermore, the DN does not just do rote learning. Each teacher only teaches *piece-meal* knowledge, (e.g., report the same cognition for “young cat” and “kitten”), but the teacher did not indicate how such a piece of knowledge should be transferred to many other equivalent settings (e.g., infinitely many possible sensory sequences which contains “young cat” or “kitten”). The DN transfers such a piece-meal knowledge to future all possible (infinitely many) equivalent input sequences although it has only seen one of such sequences, as we discussed above about the power of FA. Any DN can do such transfers automatically because of the brain-inspired architecture of the DN. Prior neural networks and any conventional databases cannot do that, regardless how much memory they have.

5.2. *GDN optimally performs while frozen*

Suppose that the $\mathbf{x}$ and $\mathbf{z}$ codes for the FA are similar to those from the real physical world. This is important for the skills learned from FA to be useful for the real physical world. The number of symbols in Σ is finite, but the number of images $\mathbf{x} \in X$ (e.g., images on the retina) from the real physical world is unbounded, although finite at any finite age if the video stream is sampled at a fixed sampling rate (e.g., 30Hz).

The following is the text version of Theorem 2.

Suppose that the GDN learning is frozen after learning the FA but still run (generating responses) by taking sensory inputs beyond those of the FA, the DN generalizes optimally. It generates the Maximum Likelihood (ML) internal responses and actions based on its experience of learning the FA.

The GDN “lives” in the real world and generalizes optimally, going beyond the FA.

5.3. *GDN optimally performs while learning*

The following is the text version of Theorem 3.

Suppose that the GDN has run out of its new Y neurons as soon as it has finished simulating the FA. If it still learns by updating its adaptive part, the DN generalizes (“thinks”) optimally by generating the ML internal responses and actions based on the limited network resource, the limited skills from FA, and real-world learning up to the last network update.

Such a unified, general-purpose, task nonspecific, incremental, immediate learning DP can potentially develop a DN to learn a subset of human society’s knowledge as an FA, but each DN it develops only learns one such FA in its lifetime. Many DNs learn and live through their own career trajectories to become many different experts who also share the common sense knowledge of the human society. The human programmer of a DP does not need to know the meanings of the states of each possible FA, which are only in the minds of the future human teachers and the learned DNs.

The following gives additional detail about how a GDN simulates any FA.

6. Additional Details

First consider the mapping from symbolic sets Σ and Q, to vector spaces X and Z, respectively.

A symbol-to-vector mapping m is a mapping $m : \Sigma \mapsto X$. We say that $\sigma \in \Sigma$ and $\mathbf{x} \in X$ are equivalent, denoted as $\sigma \equiv \mathbf{x}$, if $\mathbf{x} = m(\sigma)$.

A binary vector of dimension d is such that all its components are either 0 or 1. It simulates that each neuron, among d neurons, either fires with a spike ($s(t) = 1$) or without ($s(t) = 0$) at each sampled discrete time $t = t_i$.

Let the motor area Z consist of several concept zones, $Z = (Z_1, Z_2, ..., Z_n)$. Within each concept zone only one neuron can fire. For example, each neuron represents a particular amount of contraction of a muscle or the degree of a joint. Neurons in each concept zone compete so that only the winner neuron can fire. If only one concept zone can fire at any time, the GDN can simulate any deterministic FA (DFA). If any number of concept zones can fire at any time, the GDN can simulate any nondeterministic FA (NFA).

If the pre-response value of the winner neuron is higher than a dynamic threshold, then the winner neuron fires. Otherwise, the winner neuron does not fire, like other loser neurons in the same concept zone. The value of the dynamic threshold in each concept zone can change according to the modulatory system (e.g., affected by punishment, reward, and novelty). In the proof of Theorem 1, the dynamic threshold is machine zero, which accounts for the amount of computer round-off noise.

Although each concept zone has only one or no neuron firing at any time, different concept zones can fire in parallel. For example, Z_1 represents the location and Z_2 represents the type of an object. Suppose that each concept zone has 4 positive values plus one value "do-not-care" (when all neurons in a concept zone do not fire), then n motor concepts amounts to 5^n possible actions, exponential in the number of concepts n. A symbolic model requires 5^n state symbols, but the motor area Z needs only $4n$ neurons.

7. Experiments with DN

Our DN had several versions of experimental embodiments, from networks for general object recognition from $360°$ views [22], to Where-What Networks that detect (in free viewing), recognize, find (given type or location), multiple objects from natural complex backgrounds [23], to Multilayer In-place Learning Networks (MILN) that learn and process text of natural language [48] (e.g., the part-of-speech tagging problem and the chunking problem using natural languages from the Wall Street Journal), to Where-What Networks that incrementally acquire early language from interactions with environments and also generalize [29]. Preliminary versions of the DN thinking process has been observed by [25], [24] for vision as the DN predicts while learning, and by [29] for language acquisition as the DN predicts across categories and superset and subset while learning. However, the impressive results from such DNs are difficult to understanding without a clear theoretical framework here that links DNs with the well-known automata theory and the mathematical properties presented as the three theorems.

8. Discussions

When the complex nature like the brain-mind has been explained in terms of precise mathematics, the complex nature can be better understood by more analytically trained researchers, regardless their home disciplines.

The DN model develops a "brain" internal mapping $X(t-1) \times Z(t-1) \mapsto X(t) \times Z(t)$ to explain the real-time external brain functions. All SNs are special cases of DN in the following sense: An SN allows humans to handcraft its base net, but a DN does not. In other words, an SN is a human handcrafted model outside the brain, while DN is emergent like the brain inside its closed skull.

Using an SN, the human written symbolic text to define each node is for consensual communications among humans only. The machine that runs the SN does not truly understand such symbolic text. Mathematically, an SN uses handcrafted symbols in Q to sample the vector space Z and uses handcrafted feature detectors to get a symbolic feature set Σ as samples in X. Probabilistic variants of SN do not change the handcraft nature of the base net from Q and Σ. SNs are brittle in real physical world due to the static natures of the symbols, since these symbols are ineffective to sample an exponential number of sensory images for X and an exponential number of effector images for Z.

Conventional emergent networks, feed-forward and recurrent, were motivated by brain-like uniform, numeric, neuronal computations. However, their learning is slow, not exact, and they do not abstract well.

A GDN is also an emergent network, but is inspired more by characteristics of internal brain area Y as discussed in [43]. It learns any complex FA, DFA or NFA, immediately and error-free, through incremental observation of state transitions of the FA one at a time, using a finite memory. In particular, the GDN immediately generalizes, error-free, to many sensorimotor sequences that it has not observed before but are state-equivalent. There are no local minima problems typically associated with a traditional emergent recurrent network, regardless how complex the FA is. This means that GDN as an emergent network can abstract as well as any FA, logic and neat. This indicates that we have passed "neural networks do not abstract well".

The GDN theory is also a solution to many well known nonlinear system problems that are well known in electrical engineering and mathematics.

After learning the FA as scaffolding, the GDN can freeze its learning and optimally generalize, in the sense of maximum likelihood, for infinitely many input images arising from the real physical world. Alternatively, the GDN can continue to learn and optimally think, in the sense of maximum likelihood, by taking into account all past experience in a resource limited way. In particular, there seems no need for the human programmer to handcraft rigid internal structures, such as modules and hierarchies, for extra-body concepts. Such structures should be emergent and adaptive. For example, the input fields of every neuron should be emergent and adaptive, through mechanisms such as synaptic maintenance (see, e.g., Wang et al. 2011 [42]). This array of properties indicates that GDN as a new kind of neural networks goes beyond FA and their probability variants SNs.

Much future work is needed along the line of GDN autonomous thinking, such as the creativity of GDN, in the presence of complex backgrounds that are not directly related to the current task or goal.

Acknowledgment

The author would like to thank Z. Ji, M. Luciw, K. Miyan and other members of the Embodied Intelligence Laboratory at Michigan State University, as well as Q. Zhang and other members of the Embodied Intelligence Laboratory at Fudan University whose work have provided experimental supports for the theory presented here.

REFERENCES

[1] J. R. Anderson. *Rules of the Mind*. Lawrence Erlbaum, Mahwah, New Jersey, 1993.

[2] G. Cybenko. Approximations by superpositions of sigmoidal functions. *Mathematics of Control, Signals, and Systems*, 2(4):303–314, December 1989.

[3] R. Desimone and J. Duncan. Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, 18:193–222, 1995.

[4] A. Fazl, S. Grossberg, and E. Mingolla. View-invariant object category learning, recognition, and search: How spatial and object attention are coordinated using surface-based attentional shrouds. *Cognitive Psychology*, 58:1–48, 2009.

[5] D. J. Felleman and D. C. Van Essen. Distributed hierarchical processing in the primate cerebral cortex. *Cerebral Cortex*, 1:1–47, 1991.

[6] P. Frasconi, M. Gori, M. Maggini, and G. Soda. Unified integration of explicit knowledge and learning by example in recurrent networks. *IEEE Trans. on Knowledge and Data Engineering*, 7(2):340–346, 1995.

[7] K. Fukushima. Cognitron: A self-organizing multilayered neural network. *Biological Cybernetics*, 20:121–136, 1975.

[8] K. I. Funahashi. On the approximate realization of continuous mappings by neural networks. *Neural Network*, 2(2):183–192, March 1989.

[9] C. R. Gallistel. Themes of thought and thinking. *Science*, 285:842–843, 1999.

[10] D. George and J. Hawkins. Towards a mathematical theory of cortical micro-circuits. *PLoS Computational Biology*, 5(10):1–26, 2009.

[11] S. Grossberg. Adaptive pattern classification and universal recoding: I. parallel and coding of neural feature detectors. *Biological Cybernetics*, 23:121–131, 1976.

[12] G. E. Hinton, S. Osindero, and Y-. W. Teh. A fast learning algorithm for deep belief nets. *Neural Computation*, 18:1527–1554, 2006.

[13] J. E. Hopcroft, R. Motwani, and J. D. Ullman. *Introduction to Automata Theory, Languages, and Computation*. Addison-Wesley, Boston, MA, 2006.

[14] J. J. Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences of the USA*, 79(8):2554–2558, 1982.

[15] K. Hornik, M. Stinchcombe, and H. White. Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5):359–366, November 1989.

[16] J. M. Iverson. Developing language in a developing body: the relationship between motor development and language development. *Journal of child language*, 37(2):229–261, 2010.

[17] E. M. Izhikevich. *Dynamical Systems in Neuroscience*. MIT Press, Cambridge, Massachusetts, 2007.

[18] M. I. Jordan and C. Bishop. Neural networks. In A. B. Tucker, editor, *CRC Handbook of Computer Science*, pages 536–556. CRC Press, Boca Raton, FL, 1997.

[19] M. L. Jordan. Attractor dynamics and parallelism in a connectionist sequential machine. In *Proc. the eighth annual conference of the cognitive science society*, pages 531 – 546, Hillsdale, 1986.

[20] U. R. Karmarkar and D. V. Buonomano. Timing in the absence of clocks: encoding time in neural network states. *Neuron*, 53(3):427–438, 2007.

[21] J. E. Laird, A. Newell, and P. S. Rosenbloom. Soar: An architecture for general intelligence. *Artificial Intelligence*, 33:1–64, 1987.

[22] M. Luciw and J. Weng. Top-down connections in self-organizing Hebbian networks: Topographic class grouping. *IEEE Trans. Autonomous Mental Development*, 2(3):248–261, 2010.

[23] M. Luciw and J. Weng. Where What Network 3: Developmental top-down attention with multiple meaningful foregrounds. In *Proc. IEEE Int'l Joint Conference on Neural Networks*, pages 4233–4240, Barcelona, Spain, July 18-23 2010.

[24] M. Luciw and J. Weng. Where What Network 4: The effect of multiple internal areas. In *Proc. IEEE 9th Int'l Conference on Development and Learning*, pages 311–316, Ann Arbor,, August 18-21 2010.

[25] M. Luciw, J. Weng, and S. Zeng. Motor initiated expectation through top-down connections as abstract context in a physical world. In *IEEE Int'l Conference on Development and Learning*, pages +1–6, Monterey, CA, Aug. 9-12 2008.

[26] M. D. Mauk and D. V. Buonomano. The neural basis of temporal processing. *Annual Review of Neuroscience*, 27:307–340, 2004.

[27] J. L. McClelland, D. E. Rumelhart, and The PDP Research Group, editors. *Parallel Distributed Processing*, volume 2. MIT Press, Cambridge, Massachusetts, 1986.

[28] M. Minsky. Logical versus analogical or symbolic versus connectionist or neat versus scruffy. *AI Magazine*, 12(2):34–51, 1991.

[29] K. Miyan and J. Weng. WWN-Text: Cortex-like language acquisition with What and Where. In *Proc. IEEE 9th Int'l Conference on Development and Learning*, pages 280–285, Ann Arbor, August 18-21 2010.

[30] V. Müller. The hard and easy grounding problems. *AMD Newsletter*, 7(1):8–9, 2010.

[31] B. A. Olshaushen and D. J. Field. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature*, 381:607–609, June 13 1996.

[32] C. W. Omlin and C. L. Giles. Constructing deterministic finite-state automata in recurrent neural networks. *Journal of the ACM*, 43(6):937–972, 1996.

[33] W. K. Purves, D. Sadava, G. H. Orians, and H. C. Heller. *Life: The Science of Biology*. Sinauer, Sunderland, MA, 7 edition, 2004.

[34] T. T. Rogers and J. L. McClelland. Preecis of semantic cognition: A parallel distributed processing approach. *Behavioral and Brain Sciences*, 31:689–749, 2008.

[35] D. E. Rumelhart, J. L. McClelland, and the PDP Research Group. *Parallel Distributed Processing*, volume 1. MIT Press, Cambridge, Massachusetts, 1986.

[36] T. Serre, L. Wolf, S. Bileschi, M. Riesenhuber, and T. Poggio. Robust object recognition with cortex-like mechanisms. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 29(3):411–426, 2007.

[37] M. Sur and J. L. R. Rubenstein. Patterning and plasticity of the cerebral cortex. *Science*, 310:805–810, 2005.

[38] J. B. Tenenbaum, V. de Silva, and J. C. Langford. A global geometric framework for nonlinear dimensionality reduction. *Science*, 290:2319–2323, 2000.

[39] J. B. Tenenbaum, T. L. Griffithsb, and C. Kemp. Theory-based bayesian models of inductive learning and reasoning. *Trends in Cognitive Sciences*, 10(7):309–318, 2006.

[40] J. B. Tenenbaum, C. Kemp, T. L. Griffiths, and N. D. Goodman. How to grow a mind: Statistics, structure, and abstraction. *Science*, 331:1279–1285, 2011.

[41] L. S. Vygotsky. *Thought and language*. MIT Press, Cambridge, Massachussetts, 1962. trans. E. Hanfmann & G. Vakar.

[42] Y. Wang, X. Wu, and J. Weng. Synapse maintenance in the where-what network. In *Proc. Int'l Joint Conference on Neural Networks*, pages +1–8, San Jose, CA, July 31 - August 5 2011.

[43] J. Weng. A 5-chunk developmental brain-mind network model for multiple events in complex backgrounds. In *Proc. Int'l Joint Conf. Neural Networks*, pages 1–8, Barcelona, Spain, July 18-23 2010.

[44] J. Weng. Three theorems about developmental networks and the proofs. Technical Report MSU-CSE-11-9, Department of Computer Science, Michigan State University, East Lansing, Michigan, May,12 2011.

[45] J. Weng. Three theorems: Brain-like networks logically reason and optimally generalize. In *Proc. Int'l Joint Conference on Neural Networks*, pages +1–8, San Jose, CA, July 31 - August 5 2011.

[46] J. Weng. Symbolic models and emergent models: A review. *IEEE Trans. Autonomous Mental Development*, 3:+1–26, 2012. Accepted and to appear.

[47] J. Weng, J. McClelland, A. Pentland, O. Sporns, I. Stockman, M. Sur, and E. Thelen. Autonomous mental development by robots and animals. *Science*, 291(5504):599–600, 2001.

[48] J. Weng, Q. Zhang, M. Chi, and X. Xue. Complex text processing by the temporal context machines. In *Proc. IEEE 8th Int'l Conference on Development and Learning*, pages +1–8, Shanghai, China, June 4-7 2009.

[49] Y. Yamashita and J. Tani. Emergence of functional hierarchy in a multiple timescale neural network model: a humanoid robot experiment. *PLoS Computational Biology*, 4(11):e1000220, 2008.

Paper

Discovery of Concept Cells in the Human Brain – Could It Change Our Science?

Asim Roy[*]

Arizona State University

[*] *corresponding author*: asim.roy@asu.edu

Abstract

Neuroscientists have recently discovered single cells in the human brain that have highly selective, abstract and invariant responses to complex, natural stimuli. They call these cells "concept cells." This discovery is from single cell recordings from the brains of epilepsy patients at UCLA medical school. Various types of experiments have been performed with these patients over the last few years and they have firmly established the existence of these cells and the nature of information encoded by them. Here I summarize these experiments and findings and try to explain what they might mean for our theories and our science. For example, these experiments show that concept cells have meaning at the cognitive level. The simple fact that meaning could be encoded in a single concept cell and so easily accessible could have a profound impact on our sciences. It also brings into question the nature of representation of concepts at the higher cognitive levels.

1. Introduction

Neuroscientists have recently discovered cells in the medial temporal lobe (MTL) region of the human brain that have highly selective response to complex stimuli (Cerf et al. 2010, Fried 1997, Gelbard-Sagiv et al. 2008, Koch 2011, Kreiman et al. 2000, Pedreira et al. 2010, Quian Quiroga et al. 2005, 2008, 2009, 2010a, 2010b, Viskontas et al. 2009 and others). They call these cells "concept cells." These concept cells show that single cells can encode substantial information about single objects and concepts. For example, they found one hippocampal neuron in an epilepsy patient that responded only to photos of actress Jennifer Aniston, but not to pictures of other blonde women or actresses. Moreover, the same hippocampal neuron fired in response to seven very different pictures of Jennifer Aniston. The findings also provide insight about the process by which these concept cells form in the brain. They discovered that concept cells are created within a very short span of time and in response to repeated firings of certain neurons. For example, concept cells were created in a matter of days in the brains of epilepsy patients to recognize the researchers in the hospital who were performing experiments with them. They also found neurons, which they call triple invariant neurons, which responded not only to the image of a person or object, but also to the persons spoken and written names.

In addition, they could link the "thought" of a patient about certain objects and persons to certain concept cells without the patient actually verbalizing the "thought." For example, from the firings of these concept cells, they could figure out whether the patient was thinking about Jennifer Aniston or tall buildings like the Eiffel Tower. All these findings could have a profound impact on our understanding of the brain and how it works – from knowledge representation and learning processes to where and in what form "meaning" might reside in the brain.

In this article, I summarize the experiments and findings, of a group of neuroscientists at UCLA (University of California, Los Angeles, USA) under the leadership of Itzhak Fried and Caltech (California Institute of Technology, Pasadena, CA, USA) under the leadership of Christof Koch, that have been reported in a number of recent articles and papers (Cerf et al. 2010, Fried et al. 1997, Gelbard-Sagiv et al. 2008, Koch 2011, Kreiman et al. 2000, Pedreira et al. 2010, Quian Quiroga et al. 2005, 2008, 2009, 2010a, 2010b, Viskontas et al. 2009 and others). We also characterize the nature of these concept cells and how they conflict with our current understanding of the brain.

The article is organized as follows. Section 2 summarizes the recent evidence for concept cells. Section 3 provides some insight on the nature and properties of these cells and how they conflict with our current theories of the brain. Section 4 has the conclusions.

2. Concept cells in the human brain

2.1 Single cell recording

The Seizure Disorder Center in the David Geffen School of Medicine at UCLA, directed by Dr. Itzhak Fried, is one of the handful of clinics in the world where single cell recordings are performed. To find the source of seizures, about a dozen or so depth electrodes are implanted in the brains of epilepsy patients and left in place for about a week and their signals monitored (Fried et al. 1997). They have developed a special type of hollowed electrode through which they insert nine microwires to pick up signals from 10 to 50 neurons using a number of recording channels. A majority of the electrodes are placed in the medial temporal lobe (MTL) region of the brain because most seizures originate there. The MTL consists of many hierarchically interconnected areas including the hippocampus, amygdala, parahippocampal cortex, and entorhinal cortex, and is understood to turn visual and other sensory percepts into declarative memories.

2.2 Finding concept cells - the experimental procedure

The concept cell experiments are done on the side while the patients wait for a seizure with the electrodes hooked up. Generally, this is the procedure they (the researchers) use to find concept cells in the brains of the patients. They interview the patients to find out about the places they know and have visited, movies and TV shows they have seen and various other things they might be familiar with. The basic idea is to find out what objects, people and places an individual patient might have memories of. From such an interview, they will make a list (inventory) of say 100 people, objects and places the individual patient might be familiar with. They will then gather the images of people, places and objects that an individual patient is familiar with and show them to the patient. And they monitor the activity (firing) of the neurons while these images are shown.

2.3 Concept cells – their highly selective response to complex stimuli

Years of research has shown that MTL neurons respond selectively to complex visual stimuli and represent visual information in an abstract way (Quian Quiroga et al. 2008). For example, MTL neurons were found to respond selectively to gender and facial expression (Fried et al. 1997) and to pictures of particular categories of objects, such as animals, faces and houses (Kreiman et al. 2000). Quian Quiroga et al. (2008) reports finding a single cell in the right anterior hippocampus of a patient that responded selectively to pictures of the actor Steve Carrel. They also found that “one neuron in the hippocampus of another patient was activated by pictures of Jennifer Aniston and Lisa Kudrow, both actresses in the TV series ‘Friends’, whereas another neuron in the parahippocampal cortex fired to pictures of the Tower of Pisa and the Eiffel Tower, but not to other landmarks.” They note that in these examples the stimuli to which the particular neurons responded were clearly related. In Quian Quiroga & Kreiman (2010a), they report finding a neuron firing to two different basketball players, a neuron firing to Luke Skywalker and Yoda, both characters of Star Wars, and another firing to a spider and a snake (but not to other animals).

Quian Quiroga et al. (2008) call these single cell representations, whatever they represent, an explicit representation. (Here’s a personal clarification from Christof Koch on explicitness: “Explicit here is meant in the sense of Crick and Koch, in which an explicit representation is one in which a simple decoder, such as a perceptron, can infer the identity of the stimulus. Indeed, a simple linear classifier applied to the spiking activity of a handful of simultaneously recorded units predicted which picture the patient was seeing in each trial far above chance Quian Quiroga et al. (2007).”) They estimate that 40% of the responsive units in MTL are tuned to such explicit representation and can indicate whether the picture of a particular person or object is being shown. In their view, the existence of cells that respond to a single individual or category (category cells), is compatible with the thinking that there are cells that encode aspects of meaning of a particular stimulus.

2.4 Concept cells – the triple invariant ones

In their more recent experiments, reported in Quian Quiroga, Kraskov, Koch and Fried (2009), they found that single MTL neurons can encode information about the same percept that can arise in different modalities such as visual, textual and sound. For this experiment, they implanted 7 subjects with microelectrodes and recorded from 750 MTL units (335 single units and 415 multiunits; 46.9 units per session) over 16 experimental sessions. Of the 750 units, only 79 had any significant response to at least one stimulus. For the neurons that responded, they checked their modality invariance properties by showing the subjects three different pictures of the particular individual or object that a unit responded to and to their spoken and written names. In these experiments, they found “a neuron in the left anterior hippocampus that fired selectively to three pictures of the television host Oprah Winfrey and to her written (stimulus 56) and spoken (stimulus 73) name…. To a lesser degree, the neuron also fired to the actress Whoopi Goldberg.” They also found a neuron in the entorhinal cortex of a subject that responded “selectively to pictures of Saddam Hussein as well as to the text ‘Saddam Hussein’ and his name pronounced by the computer….. There were no responses to other pictures, texts, or sounds.”

A most interesting finding is about the researchers who conducted these experiments and how they were quickly encoded as a percept in the MTL. They found a neuron in the amygdala that was “selectively activated by photos, text, and sound presentations of one of the researchers performing recordings with the patient at UCLA…...Altogether, we found five units responding to one or more researchers performing experiments at UCLA….None of these researchers were previously known to the patient, thus indicating that MTL neurons can form invariant responses and dynamic associations—linking different individuals into the same category ‘the researchers at UCLA’—within a day or so.” The authors call these neurons “triple invariant” neurons and they were those that had the visual invariance property and also had significant responses to spoken and written names of the same person or object. They found 17 of the 79 responsive units to have such triple invariance property. They report that “Eleven of the neurons showing triple invariance responded to only one person and the remaining six responded to more than one person or object.” They conclude that these findings show that information from different sensory modalities converges onto neurons in the MTL.

2.5 Concept cells – how the brain selects what concepts (people, places, objects) to encode

In a very recent article, Cristof Koch nicely described some of the experiments and their findings (Koch 2011). Here’s

Koch is his own words: “We enlisted the help of several epileptic patients. While they waited for their seizures, we showed them about 100 pictures of familiar people, animals, landmark buildings and objects. We hoped one or more of the photographs would prompt some of the monitored neurons to fire a burst of action potentials. Most of the time the search turned up empty-handed, although sometimes we would come upon neurons that responded to categories of objects, such as animals, outdoor scenes or faces in general. But a few neurons were much more discerning. One hippocampal neuron responded only to photos of actress Jennifer Aniston but not to pictures of other blonde women or actresses; moreover, the cell fired in response to seven very different pictures of Jennifer Aniston. We found cells that responded to images of Mother Teresa , to cute little animals and to the Pythagorean theorem, a2 + b2 = c2.”

Nobody is obviously born with cells selective of Jennifer Aniston or Mother Teresa. So the obvious question is: When and how are these selective cells (concept neurons) created in the brain? From Koch (2011) again: “Every time you encounter a particular person or object, a similar pattern of spiking neurons is generated in higher-order cortical regions. The networks in the medial temporal lobe recognize such repeating patterns and dedicate specific neurons to them. You have concept neurons that encode family members, pets, friends, co-workers, the politicians you watch on TV, your laptop, that painting you adore….Conversely, you do not have concept cells for things you rarely encounter, such as the barista who just handed you a nonfat chai latte tea.”

2.6 Concept cells – associating thoughts with concept cells

The most profound findings come from recent experiments that show that one can actually regulate the firings of these concept cells just by consciously thinking about the associated objects. Here’s Koch’s description of the experiments and findings (Koch 2011): “More recently, Moran Cerf and others from my lab, together with Fried, hooked several concept cells to an ex¬ternal display to visualize a patient’s thoughts..… Let me walk you through one example. Cerf recorded from a neuron that fired in response to images of actor Josh Brolin (whom the patient knew from her favorite movie, The Goonies) and from another neuron that fired in response to the Marilyn Monroe scene I just mentioned. The patient looked at a monitor where these two images were superimposed, with the activity of the two cells controlling the extent to which she saw Brolin or Monroe in the hybrid image…..Whenever the patient focused her thoughts on Brolin, the associated neuron fired more strongly. Cerf arranged the feedback such that the more this cell fired relative to the other one, the more visible Brolin became and the more the image of Monroe faded, and vice versa. The image on the screen kept changing until only Brolin or only Monroe remained visible and the trial was over.”

3. Concept cells - their properties and their meaning

These recent findings in neuroscience obviously raise many questions and could have many different interpretations. In this section, I try to characterize these “concept cells” to get a better understanding of the nature of these cells.

3.1 Some general properties of concept cells

3.1.1 Selective response

As these findings indicate, the foremost property of MTL concept cells is that they respond selectively, some to a very broad class of stimuli (e.g. a category cell that responds to a broad class of objects) whereas others to a smaller class of stimuli. A smaller class may include stimuli from one or more very closely related objects (e.g. Jennifer Aniston and Lisa Kudrow, Tower of Pisa and the Eiffel Tower, spiders and snakes), and, for some triple invariant neurons, that class of stimuli may just include different views of an object (or person) and its written and spoken name. Although they never test these concept cells with an exhaustive set of images of objects and people to claim with certainty that a certain cell responds only to one or a few objects, such as Jennifer Aniston, they do test for other closely related objects to narrow down the selectivity of the response. So, for example, for a cell responding to Jennifer Aniston, they test whether it responds to other blonde actresses or not. Although not exhaustive, that’s a good verification of selectivity of the cell. (Here’s a personal clarification from Christof Koch on why no exhaustive testing is done: “It is not because we don’t want to but because we typically have 30-60 min per session with a patient and the space of possible images is gigantic. Thus, as we need to show each image 6 times to obtain some statistical significance, we can typically only show about 100 different pictures in a single session.”)

3.1.2 Encodes a high level abstraction

A second property of some MTL concept cells is that they encode an abstraction that differentiates a particular set of very closely related objects from others within a broader class of such objects. For example, Koch (2011) reports finding a hippocampal neuron that responded only to photos of actress Jennifer Aniston but not to pictures of other blonde women or actresses. Thus, this particular concept cell discovered an abstraction that differentiated Jennifer Aniston, and perhaps a few other ones along with her (e.g. Lisa Kudrow), from other blonde women actresses although they are all in the same broad category. In other words, the particular hippocampal neuron did not encode a feature common to any one of the categories “blonde,” “women” and “actresses.” Quian Quiroga et al. (2010b) had the following observation: “…. one could still argue that since the pictures the neurons fired to are related, they could be considered the same concept, in a high level abstract space: “the basketball players,” “the landmarks,” “the Jedi of Star Wars,” and so on.” Some MTL concept cells, in fact, encode very high level abstractions that are modality invariant and can distinguish a very small set of objects, perhaps even a single object, within a broader class of such objects. Here's a related observation from Quian Quiroga et al. (2010b): "…. these neurons show a very abstract representation, firing selectively to completely different pictures of the same person: for example, a neuron in the hippocampus fired to seven different pictures of Jennifer Aniston but not to 80 other pictures of different people, objects, or animals (Quian Quiroga et al., 2005). This level of abstraction goes beyond a specific sensory modality since these neurons can also selectively fire to the person's written and spoken names (Quian Quiroga et al., 2009)."

3.1.3 Concept cells created on a need basis and for simplicity, automation and efficiency

A third property of these MTL concept cells is that they are created on a need basis and perhaps for reasons of simplicity, automation and computationally efficiency. The rapid formation of concept cells has been well observed in these experiments (Cerf et al., 2010; Koch, 2011). We again cite from Koch (2011): "Every time you encounter a particular person or object, a similar pattern of spiking neurons is generated in higher-order cortical regions. The networks in the medial temporal lobe recognize such repeating patterns and dedicate specific neurons to them. You have concept neurons that encode family members, pets, friends, co-workers, the politicians you watch on TV, your laptop, that painting you adore …..Conversely, you do not have concept cells for things you rarely encounter, such as the barista who just handed you a nonfat chai latte tea." A reasonable conjecture is that these concept cells are created in the MTL on the basis of need and for reasons of computationally efficiency. The "need" basis is fairly obvious. One doesn't need to recognize "the barista who just handed you a nonfat chai latte tea" on a long term basis. So trying to create a memory for that barrista, or the thousands of other people encountered during one's lifetime, would be a waste of resources. At this time, we obviously don't know the process by which the brain determines the "need" to remember something. Frequency of encounter with an object or person could be one criterion. Intensity of an experience, such as an accident or burn, could be another one.

From a computational efficiency point of view, consider the following factors. First, such concept cells simplify and automate the process of recognizing repeating patterns, patterns that are at a lower level and uses distributed coding. Once one or more concept cells are created, MTL no longer has to interpret the repeating patterns over and over again, where such patterns can be spread out over hundreds of thousands of neurons. Second, Quian Quiroga, Kraskov, Koch and Fried (2009) have found that certain MTL concept cells encode information about the same percept in different modalities such as visual, textual and sound (triple invariance). It is indeed computationally efficient to create and use just one single concept cell that can recognize repeating patterns, which relate to the same object or category, but arise from a variety of sensory sources. Such a setup in MTL simplifies and speeds up the identification of a concept in its various forms. It also provides a single source access to a high-level concept to other parts of the brain.

Although much of the evidence for concept cells at this time is from the MTL region, there is no reason to preclude their use in other functional areas of the brain. Existence of MTL concept cells demonstrate that the brain is capable of very high-level abstractions and that they are being used for reasons of need and efficiency. And efficiency should be a factor in the operation of other regions of the brain.

3.2 Do concept cells have meaning? Are they at the cognitive level?

A very fundamental question is whether individual concept cells have meaning at the cognitive level. The general understanding in brain sciences is that spiking neurons are at the subcognitive level and the firings of an individual neuron have no meaning at the cognitive level. In Quian Quiroga et al. (2008), they claim that concept cells have meaning: "The existence of category cells (Kreiman et al., 2000), or cells responding to single individuals (Quian Quiroga et al., 2005), is compatible with the view that they encode aspects of the meaning of any one stimulus that we might wish to remember." So we explore here in what way a concept cell has meaning.

We first summarize the experiments and results reported in Cerf et al. (2010). In their experiments, twelve epilepsy patients played a game where they controlled the display of two superimposed images. The controlling was done through the activity of four MTL neurons. Before the actual experiment, the researchers identified four different neurons in each patient that responded selectively to four different images. In these experiments, one of the four images was designated randomly as the target image. Each trial started with a short display of a random target image (say a picture of Jennifer Aniston or Marilyn Monroe) followed by an overlaid hybrid image consisting of the target and one of the other three images (designated as the distractor image; say a picture of a snake or frog). The subject was then told to enhance the target image by focusing his/her thoughts on it; as per Cerf et al. (2010), the patients were instructed to ''continuously think of the concept represented by that image." The initial visibility of both the images, target and distractor, were at 50% and the visibility of an image was increased or decreased every 100 ms based on the firing rates of the four MTL neurons that were monitored. Firing rates were measured using spike counts and used to control the visibility of the two images on the screen. In general, if the firing rate of one neuron was higher compared to the other, the image associated with that neuron became more visible and the other image became less visible. The trial was terminated when either one of the two images, the target or the distractor image, was fully visible or after a fixed time limit of 10 seconds. The subjects successfully reached the target in 596 out of 864 trials (69.0%; 202 failures and 66 timeouts).

Now to the question of whether the firings (spikes) of a high-level concept cell imply anything at the cognitive level in the sense that one can interpret it. In other words, does its firing have any implied meaning? These experiments show that there is an obvious connection between the "thinking" about an image and the firing rate of the corresponding concept cell. The more a subject thought about the concept in a target image, the higher was the firing rate of the corresponding neuron, which, in turn, caused the target image to become more visible. This shows that at least some major aspect of a mental thought was explicitly associated with a particular concept cell and caused its enhanced firings, although it might not have been the only concept cell associated with that mental thought. The appropriate adjustment of the corresponding image on the screen verified the existence of the association between the "thinking" about a particular image (target or distractor) and the corresponding concept cell. In a more simplistic interpretation, suppose image A is the target image and image B the distractor image. The enhanced firing of the particular concept cell associated with image A is essentially equivalent to the patient saying to the researcher: "I am thinking about the target image A." However, not a single word is actually spoken by the patient and the researcher can still figure out what the patient meant to say simply from the enhanced firing of the corresponding concept cell. In other words, the enhanced firing of a single concept cell had a meaningful interpretation.

These experiments verify that a concept cell can indeed have meaning at the cognitive level, in the sense that its activation (firing) can be interpreted and directly related to elements of thought of a person. What this also means is that it is not necessary to monitor, read and interpret the outputs of hundreds of thousands of neurons to verify the existence of a particular element of thought. It also means that these MTL concept cells are not just encoding a percept, but, in addition, have meaning associated with them.

3.3 Are concept cells grandmothercells?

The grandmother cell theory in neuroscience postulates that objects, such as one's grandmother, are actually represented by single neurons in the brain (Barlow 1972, 1995, Page 2000, Gross 2002). The idea of grandmother cells emerged from studies that showed different neurons respond to different stimuli Gross (2002). However, concept cells are not grandmother cells (Quian Quiroga et al. 2008, 2010a, 2010b). From Quian Quiroga et al. (2008): "Although these cells bear some similarities to 'grandmother cells', several arguments make this interpretation unlikely. First, it is implausible that there is one and only one cell responding to a person or concept because the probability of finding this cell, out of a few hundred million neurons in the MTL, would be very small." Concept cells just encode very high-level abstractions about objects and concepts in a sparse coding system.

3.4 Is finding one concept cell in a sparse representation system good enough to infer about the concept or object?

The related cells in the sparse representation of a concept are called sister cells or units (Cerf et al. 2010). The sister cells (e.g. other Jennifer Aniston concept cells) are not necessarily in contiguous locations in the brain. They could be in different hemispheres and in different regions within a hemisphere. From Cerf et al. (2010): "The subject most likely activated a large pool of neurons selective to 'Johnny Cash' even though the feedback was only based on just one such unit. We identified 8 such units in a total of 7 subjects."An obvious and relevant question about concept cells is: Since they are believed to be one of the units in the sparse representation of a concept (Lewicki 2002; Olshausen & Field 2004) and thus, theoretically, there are other concept cells (sister cells) coding for that concept (e.g. a Jennifer Aniston concept), can one infer what the object or concept is just from the activation of one such cell in the sparse representation? In the UCLA/Caltech experiments, that's what they do. In the experiments by Cerf et al. (2010), they just found one of the concept cells for an image or concept (e.g. a Jennifer Aniston or a Steve Carrel cell) and used that in their experiments to infer what object the patient was thinking about (Cerf et al. (2010): "… the feedback was only based on just one such unit."). There was no attempt to find the rest of the cells in the sparse representation of an object or concept. And they perhaps didn't even know where the rest of the cells were in that sparse representation of a particular object or concept. (Here's a personal clarification from Christof Koch on why they couldn't even attempt to find the sister cells: "Again, this makes it sound like we decided not to. But to find other sister cells, we would have to record from each of the other one billion neurons in the medial temporal lobe, hardly feasible with 100 microwires." And according to Itzhak Fried (personal communication), the "organization of "concept cells" is not columnar or topographic. Given their sparse and nontopographic distribution it would be difficult to trace them on fMRI.")

Going back to the representation issue, the question again is: Didn't they need to find and read the activations of the rest of the cells in the sparse representation of a concept and interpret the pattern as a whole before they could determine what the object or concept is? The answer is obviously no; there was no need to find the rest of the cells in that sparse representation. One can infer from the experiments by Cerf et al. (2010) that information encoded by certain concept cells is so specific to an object or concept (e.g. a triple invariant neuron) that there is no need to "find and read" the other concept neurons in the sparse representation, wherever they are, in order to determine what the object or concept is. From Quian Quiroga et al. (2008) on this issue: "This combination of selectivity and invariance leads to an explicit representation (Koch, 2004), in which a single cell can indicate whether the picture of a particular person is being shown." This definitely raises questions about the theory of distributed representation, whether in sparse or dense form, and the need to “read and interpret” patterns of activation across an ensemble of neurons.

3.5 Other quick notes

The concept cells were found in different MTL regions. For example, a “James Brolin” cell was found in the right hippocampus, a “Venus Williams” cell was in the left hippocampus, a “Marilyn Monroe” cell was in the left parahippocampal cortex and a “Michael Jackson” cell was in the right amygdala. It is possible that they represent different levels of abstractions or invariance in these different regions. However, the highest degree of invariance (across modalities), according to Itzhak Fried, was in the hippocampus and entorhinal cortex.

I raised the following issue with these scientists at UCLA/Caltech: “Even though a million cells are activated by an image of Jennifer Aniston, and say 12 of them are Jennifer Aniston concept cells, in your experiments, you tracked only one such concept cell and that was good enough. There was no need to “read out” other Jennifer Aniston concept cells, wherever they were, as would be required in a distributed representation framework.” Here’s the response from Itzhak Fried: “Yes. But I suspect more than a million cells are activated by Jennifer Aniston and they could probably be arranged on a variance scale with our "concept cells" at the extreme low. Still it is easier to find a concept cell than a Higg's boson.”

4. Conclusions

Single cell recordings from human brains are relatively new. (Christof Koch’s note: “Careful; the first such recordings were done in the 1960s. It’s only in the past decade though that such recordings can be carried out with the necessary reliability, high standards and reproducibility.”) And the experiments being performed at UCLA medical school with epilepsy patients are quite unique and generating new information about the human brain. In this article, I have tried to summarize their experiments and findings. I have also tried to characterize the nature of these concept cells based on their findings. The most interesting finding is that the firings of a concept cell can have meaning at the cognitive level. It almost seems like we can “touch and feel” parts of the brain that have meaning. Second, these experiments raise serious questions about distributed representation at higher levels of cognition. In general, these experiments and findings could have a very large impact on our thinking about knowledge representation, cognitive processes and brain theories.

Are all these findings a surprise to the neuroscience community? I asked Itzhak Fried that question. His response: “As for ‘surprises’, it is difficult to surprise the neuroscience community, but for us the explicit nature of the code on the single neuron level was a surprise.”

I conclude with this interesting quote from Waydo, Kraskov, Quiroga, Fried and Koch (2006): “Instead, it would imply that rather than a single neuron responding to dozens of stimuli out of a universe of tens of thousands, such a neuron might respond to only one or a few stimuli out of perhaps hundreds currently being tracked by this memory system, still with millions of neurons being activated by a typical stimulus. These results are consistent with Barlow’s (1972) claim that “at the upper levels of the hierarchy, a relatively small proportion [of neurons] are active, and each of these says a lot when it is active,” and his further speculation that the “aim of information processing in higher sensory centers is to represent the input as completely as possible by activity in as few neurons as possible” (Barlow, 1972).”

References

Barlow, H. (1972). Single units and sensation: A neuron doctrine for perceptual psychology. *Perception*, 1, 371–394.

Barlow, H. (1995). The neuron doctrine in perception. In *The cognitive neurosciences*, M. Gazzaniga ed., 415–436. MIT Press, Cambridge, MA.

Cerf, M., Thiruvengadam, N., Mormann, F., Kraskov, A., Quian-Quiroga, R., Koch, C. & Fried, I. (2010). Online, voluntary control of human temporal lobe neurons. *Nature*, 467, 7319, 1104-1108.

Fried, I. , McDonald, K. & Wilson, C. (1997). Single neuron activity in human hippocampus and amygdala during recognition of faces and objects. *Neuron* 18, 753–765.

Gelbard-Sagiv, H., Mukamel, R., Harel, M., Malach, R. & Fried, I. (2008). Internally Generated Reactivation of Single Neurons in Human Hippocampus During Free Recall. *Science*, 322, 5898, 96-101.

Gross, C. (2002). Genealogy of the grandmother cell. *The Neuroscientist*, 8, 512–518.

Koch, C. (2004) *The Quest for Consciousness: A Neurobiological Approach*, Roberts and Company.

Koch, C. (2011). Being John Malkovich. *Scientific American Mind*, March/April, 18-19.

Kreiman, G., Koch, C. & Fried, I. (2000) Category-specific visual responses of single neurons in the human medial temporal lobe. *Nature Neuroscience* 3, 946–953.

Lewicki, M. (2002). Efficient coding of natural sounds. *Nature Neuroscience*, 5, 356–363.

Olshausen, B., & Field, D. (2004). Sparse coding of sensory inputs. *Current Opinion in Neurobiology*, 14, 481–487.

Page, M. (2000). Connectionist modeling in psychology: A localist manifesto. *Behavioral and Brain Sciences*, 23, 443–512.

Pedreira, C., Mormann, F., Kraskov, A., Cerf, M., Fried, I., Koch, C. & Quian Quiroga, R. (2010). Responses of Human Medial Temporal Lobe Neurons Are Modulated by Stimulus Repetition. *Journal of Neurophysiology*, 103, 1, 97-107.

Quian Quiroga, R., Reddy, L., Kreiman, G., Koch, C. & Fried, I. (2005). Invariant visual representation by single neurons in the human brain. *Nature*, 435:1102–1107.

Quian Quiroga, R., Reddy, L., Koch, C., Fried, I. (2007) Decoding visual inputs from multiple neurons in the human temporal lobe. *J. Neurophysiol*. 98, 1997–2007

Quian Quiroga, R., Kreiman, G., Koch, C. & Fried, I. (2008). Sparse but not ‘Grandmother-cell’ coding in the medial temporal lobe. *Trends in Cognitive Science*, 12, 3, 87–94.

Quian Quiroga, R., Kraskov, A., Koch, C., & Fried, I. (2009). Explicit Encoding of Multimodal Percepts by Single Neurons in the Human Brain. *Current Biology*, 19, 1308–1313.

Quian Quiroga, R. & Kreiman, G. (2010a). Measuring sparseness in the brain: Comment on Bowers (2009). *Psychological Review*, 117, 1, 291–297.

Quian Quiroga, R. & Kreiman, G. (2010b). Postscript: About Grandmother Cells and Jennifer Aniston Neurons. *Psychological Review*, 117, 1, 297–299.

Viskontas, I., Quian Quiroga, R. & Fried, I. (2009). Human medial temporal lobe neurons respond preferentially to personally relevant images. *Proceedings of the National Academy Sciences*,106, 50, 21329-21334.

Waydo, S., Kraskov, A., Quian Quiroga, R., Fried, I., and Koch, C. (2006). Sparse representation in the human medial temporal lobe. *Journal of Neuroscience*, 26, 10232-10234.

Paper

Early Detection of Alzheimer's Onset with Permutation Entropy Analysis of EEG

G. Morabito[1], A. Bramanti[2], D. Labate[1], F. La Foresta[1], F.C. Morabito[1*]

[1] University Mediterranea of Reggio Calabria, DIMET, Italy
[2] University of Messina and Centro Neurolesi, Fondazione Bonino-Pulejo, Messina, Italy
**corresponding author*: morabito@unirc.it

Abstract: In this short research communication, a new bio-marker based on information theory for the early diagnosis of Alzheimer's Disease (AD) is proposed. Permutation Entropy (PE) seems, indeed, a promising feature, easily extracted from the multi-channel EEG of a patient, for both measuring the (nonlinear) complexity of the related time series and the effect of slowing which is typically observed in EEG spectra. This feature could be added to other well known bio-markers (like the ratios of spectrum power in different rhythms) in order to improve the sensibility and specificity of the diagnosis and to monitor the possible conversion from Mild Cognitive Impairment (MCI) to AD. A sample result is presented here.

A Terrible Enemy

Alzheimer's Disease (AD) is an age-related, progressing and irreversible brain illness affecting a growing number of people all over the world [4, 5, 6]. This continuous growth is due to the increase in life expectancy determining the aging of population in industrialized nations. Researchers estimate that by 2050, just in the USA, more than 15 million will have AD if no preventions become actually possible. AD slowly destroys memory and thinking skills thus implying a severe loss of cognitive functions. This unstoppable decline has a huge impact on people with AD, their families and caregivers [10]. Finally, the high direct and indirect costs related to AD generate serious concerns on its economic burden. To be able to make a correct early diagnosis of AD would have an enormous positive public health impact because of the anticipated explosion in cases [11]. This is because the number of people developing AD would be reduced or delayed thus reducing the family and financial costs of caring.

Although, recently, some progresses have been claimed in recognizing and detecting AD, the battle is far from being won. The main direction of research on AD is today to look for better and affordable ways to diagnose AD in the early stages: this can be done, in principle, detecting the earliest brain changes that may herald the onset of the biological process. These changes are believed to begin 10-20 years before clinical symptoms appear.

AD implies most neurons in the brain lose their ability to communicate because of the fragmentation of the axons. In principle, the altered electrical activity could be detected through a standard non-invasive electroencephalogram (EEG) [12, 13, 16]. Recent advances also demonstrate the interest of neuro-imaging techniques; however, the need for a massive screening of the large population at risk call for cheaper, easily repeatable and less invasive techniques than Computerized Tomography (CT) scans, PET scans or magnetic resonance imaging (MRI) inspection. Monitoring the electric brain activity of population at risk through EEG could allow to define some suitable EEG-based biomarkers (both in time and frequency domain) that possibly contain the needed information to early understand the minor brain modification then generating mild AD by Mild Cognitive Impairment (MCI). Several research groups have investigated the potential of EEG for diagnosing AD [8, 9]. Unfortunately, EEG does not achieve yet the required clinical performance in terms of both sensitivity and specificity to be accepted as a reliable technique of screening.

Effects of AD on EEG

AD is known to have three main effects on EEG [7, 8]: 1) *slowing*, i.e. the increase of the relative power of the low-frequency bands (delta, 0.5-4 Hz, and theta, 4-8 Hz), coupled with a reduction of the mean frequency (this is measured by standard Fourier analysis); 2) *complexity reduction*, i.e., a suspect increase of regularity of the signal possibly highlighted by some nonlinear measures or by standard compression ratios; 3) *loss of synchrony* of the time series representative of the electrodes' reading: this effect on synchrony can be measured by both nonlinear and linear indices [9, 14]. The idea of using EEG in order to early detect MCI-to-AD conversion is based on the extraction of some suitable biomarkers from the EEG: these extracted characteristics can be used to build a set of features that form the input to a decision system (like a Radial Basis Function NNs [1], a Spiking Neural Networks [3] or a Probabilistic Neural Networks [19]). The computational intelligence-based classification system can output a synthetic parameter estimating the probability of having either a conversion or a MCI stable state.

A recent paper [20] showed that the effects of slowing and loss of complexity in AD EEG seem to be significantly coupled: indeed, the authors present a correlation matrix that highlight the coupling between some complexity measures and the relative power in different frequency bands. In short, the authors show that the compression ratios are significantly correlated with low-frequency relative power and anti-correlated with high-frequency relative power.

Experiments at NeuroLab

Recently, in our Laboratory in Reggio, Italy, we started to work on the problem of defining some complexity measures that can be of help in AD diagnosis. We developed a tight cooperation with the *Centro Neurolesi, Fondazione Bonino-Pulejo,* Messina, Italy, a clinical centre specialized in Alzheimer's Disease and other forms of senile dementias. We defined a protocol finalized to make possible a suitable follow up for people suffering from early symptoms of cognitive decline at risk of converting from MCI to AD. We are now also following a group of normal age-matched subjects. Since the period of study started some months ago, we have not yet checked our techniques on a sufficient number of cases. However, limited to a retrospective database already available at the centre, we have focused our attention on the definition and testing of an interesting biomarker we are proposing as a novel parameter for assessing cognitive decline and differentiate normal elderly people from MCI stable and MCI converted patients. For this limited number of cases, other kinds of diagnostic exams are available, thus allowing to cross-check our results.

Computational Intelligence, Nonlinear Analysis and Early Detection of AD

EEG recordings of subject in resting condition with eyes closed are diagnostic tools routinely carried out in hospitals. Spectral power changes in different loci are believed to reflect early signs of cortical modifications. For example, alpha rhythms that are normally captured in the occipital area move towards anterior areas with the progression of AD. It is, however, difficult to keep into account a number of slight modifications without making use of specially designed algorithms and software codes that can orchestrate in a unique scenario all of the potentially available bio-markers. In our Laboratory, we aim to develop and/or improve some signal processing methods to help our clinical partner in making a correct early diagnosis of AD. In particular, we design techniques that strongly rely on Neural Networks, Fuzzy Logic, Nonlinear Analysis and Computational Intelligence. A lot of nonlinear methods have already been proposed in the literature to study EEG background activity. Various centers of excellence world-wide distributed work on these subjects: the RIKEN Brain Science Institute, Japan, is one of the most active laboratory in the field. In a small centre like our NeuroLab, we limit our objectives just to some sub-aspects of the research. Based on our previous experience on the processing of EEG of epileptic subjects, we propose the *Permutation Entropy* (PE) as an information-theoretic biomarker easy to be extracted in real time from EEG.

The role of Permutation Entropy

Aiming to extract and visualize relevant quantitative information from a high-dimensional time series, it can be of help to use symbolic dynamics. Measuring the distribution of occurrence of certain ordinal patterns in the series, we are able to quantify temporal changes of the signals' complexity as well as of the similarities and dissimilarities between their components. The concept of PE has been introduced in a seminal paper [17], as a very fast and simple algorithm to detect dynamic complexity changes in time series. The resulting parameter is robust (i.e., independent from the reference electrode), flexible and reliable. In our study, the time evolution of PE was calculated over time epochs of 10 s for overlapping moving windows, with a shift ahead of 1 s, in order to come up with a smooth profile. The coarse-graining of the original time series allows us to explore quickly the resulting symbolic sequence of motifs through well known methods from statistics and information theory. Each EEG channel was thus mapped into an m-dimensional space through an embedding procedure:

$$\mathbf{X}_i = [x(i), x(i+\tau), \ldots, x(i+(m-1)\tau)] \qquad (1)$$

with m being the "embedding dimension" and being τ the "time lag". For every t, the real values of $\mathbf{X}_i$ were arranged in an increasing order:

$$[x(i+(k_1-1)\,\tau) \leq x(i+(k_2-1)\,\tau) \leq \ldots \leq x(i+(k_m-1)\,\tau)]. \quad (2)$$

Each vector $\mathbf{X}_i$ is then uniquely mapped onto a vector $(k_1, k_2, \ldots, k_m)$, which is one of the m! possible permutations of m distinct symbols (1, 2, … , m). The probability distribution of the permutations, obtained during the sorting process of all vectors $\mathbf{X}_i$, is indicated as p_i. PE was then calculated as:

$$H_p(m) = \Sigma_j\, p_j \ln(1/p_j) = -\Sigma_j\, p_j \ln p_j \qquad (3),$$

i.e., it represents the Shannon Entropy (SE) of the different symbols. Typically, $H_p(m)$ is normalized to its maximum $ln\,(m!)$. Accordingly, we have:

$$0 \leq H_p = H_p(m)/ln(m!) \leq 1 \qquad (4).$$

H_p can be interpreted as a measure of the distance of the time series at hand from a completely random one. A small value of H_p is indicative of a regular behaviour of the signal. The design parameters m and τ are subject to a sensitivity analysis to define their optimal values. Our investigations show that the optimal values of m and τ are not patient-dependent.

PE represents a simple yet efficient tool to assess the dynamical behaviour of the EEG [15]. If the original reading is very irregular, its power spectrum will contain more high frequency components; in the case of regular behaviour, low frequency will be preferred. For τ = 1, PE is a monotonically growing function of frequency. For example, some typical values of PE for the different rhythms of a healthy subject are: 0.53 – 0.56 (delta); 0.58-0.62 (theta); 0.68 – 0.72 (alpha); 0.73 – 0.78 (beta).

The idea of proposing PE as an EEG-based biomarker to quantify the probability of conversion MCI → AD is founded on the two following considerations:

1) The effect of *slowing* can be indirectly measured by PE since a reduction of the mean frequency of the power spectrum also implies a reduction of PE;
2) The complexity of the time series is reduced as the signal becomes more regular: the changes in the dynamics of AD brain caused by loss of neuronal synapses, axonal fragmentation and cortical atrophy has the consequence, among others, of simplifying the reading of EEG channels, that appear more repetitive including less dissimilarities among successive epochs.

The increased regularity and decreased complexity in the EEGs of AD patients reflect an anomalous connectivity of parts of the brain. Considering the results achieved by the use of PE, the abnormalities found in EEG dynamics could derive from anatomical disconnections among different cortical regions. The use of PE seems to highlight the interrelations between two aspects of the EEG changes normally analysed separately. However, the above comment suggests that the study of synchrony among the time signals of PE could possibly unveil a third correlation.

Results

In Figure 1, we report an example of the results achieved with the above described analysis. The PE is shown to change significantly in the three different cases of AD patient, MCI and control subject. The complete description of the results is the subject of a thesis and will be soon published [18]. A statistical analysis on a well conceived database of cases is, however, needed to substantiate the hypothesis presented in this research also in order to measure the specificity of the technique [2].

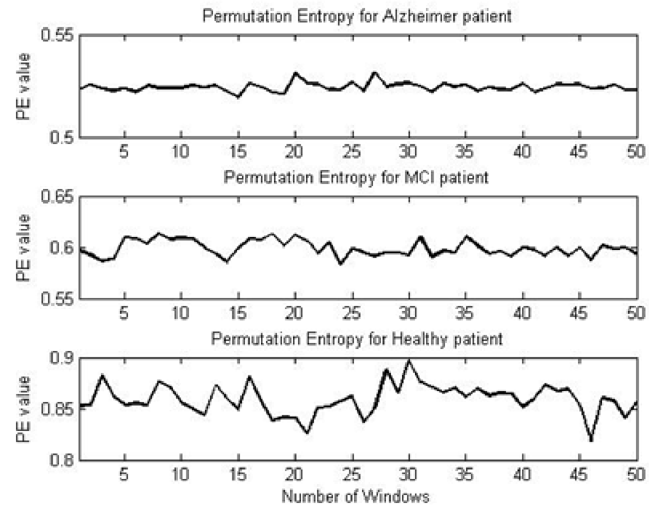


Figure 1: The time evolution of the proposed complexity measure (PE) for one electrode of the EEG 10-20 standard system. The plots report the PE values computed on 50 overlapping windows of 10 s each. The available time series is down-sampled from 1024 Hz to 256 Hz.

References

[1] Ahmadluo M., Adeli H., Adeli A., New diagnostic EEG markers of the Alzheimer's disease using visibility graph, *J. of Neural Transm*, Vol. 11, pp.1099-1109, 2001.

[2] Vialatte F. B., Dauwels J., Maurice M., Musha T. and Cichocki A., Improving the specificity of EEG for diagnosing Alzheimer's Disease, *Intl. J. of Alzheimer's Disease*, Vol. 2011

[3] Adeli H., Ghosh-Dastidar S., Dadmehr N. A wavelet-chaos methodology for analysis of EEGs and EEG sub-bands to detect seizure and epilepsy, *IEEE Trans. on Biom. Eng*., Vol. 54, No.12, pp.205-211, 2007.

[4] Berchtold N.C., Cotman C.W., Evolution in the conceptualization of dementia and Alzheimer's disease: Greco-Roman period to the 1960s. *Neurobiol. Aging*, Vol 19, No.3, pp. 173–89, 1998.

[5] Katzman R., Terry R. D., K.L. Bick, Eds., Alzheimer's disease: senile dementia and related disorders, Aging, Vol.7, New York: Raven Press, pp. 595, 1978.

[6] Boller F., Forbes M.M., History of dementia and dementia in history: an overview. *J. Neurol. Sci.* Vol. 158 No. 2, pp. 125–33, 1998.

[7] Jeong J., EEG Dynamics in patients with Alzheimer's disease. *Clinical Neurophysiology* 115, 1490-1505, 2004.

[8] Dauwels J., Vialatte F., Cichocki A., 2010. Diagnosis of Alzheimer's Disease from EEG Signals: Where Are we standing? *Current AD Research*, in press.

[9] Cichocki A., Shishkin SL., Musha T., Leonowicz Z., Asada T., Kurachi T., EEG filtering based on blind source separation (BSS) for early detection of Alzheimer's disease. *Clinical Neurophysiology* 116, 729-737, 2005.

[10] Mattson MP., Pathways towards and away from Alzheimer's disease. *Nature* 430, 631-639, 2004.

[11] Park A., Alzheimer's unlocked, *Time*, October 25, 31-35, 2010.

[12] Tiraboschi P, Hansen LA, Thal LJ, Corey-Bloom J, The importance of neuritic plaques and tangles to the development and evolution of AD. *Neurology* Vol. 62, No.11, 1984–9, 2004.

[13] Rangayyan RM., *Biomedical Signal Analysis*, IEEE Press, 2002.

[14] Dauwels J., Vialatte F.B., Musha T., Cichocki A. A comparative study of synchrony measures for the early diagnosis of Alzheimer's disease based on EEG , *Neuroimage*, Vol.49, pp.668-693, 2010.

[15] Olofsen E., Sleigh JW., Dahan A., Permutation entropy of the electroencephalogram: a measure of anaesthetic drug effect. *British J. of Anaesthesia,* Vol.101, No.6, pp.810-21, 2008.

[16] Sanei S., Chambers J.A., *EEG Signal Processing*, John Wiley & Sons, 2007.

[17] Bandt C., Pompe B., Permutation entropy, a natural complexity measure for time series, *Phys. Rev. Lett*., Vol.88, No.17, 174102, 2002.

[18] Morabito G., Early diagnosis of AD from EEG, Laurea Degree Thesis (in Italian), 2011.

[19] Sankari Z., Adeli H., Probabilistic neural networks for diagnosing of AD using conventional and wavelet coherence, *J. of Neuroscience Methods*, Vol. 197, pp. 163-170, 2011.

[20] Dauwels J., Srinivasan K., et al, Slowing and loss of complexity in Alzheimer's EEG: two sides of the same coin?, *Intl. J.of Alzheimer's Disease*, Vol. 2011.

2011 INNS Awards

By Leonid Perlovsky, Ph.D.
Chair of the Awards Committee of the INNS

As the chair of the Awards Committee of the INNS, I am pleased and proud to announce the recipients of the 2011 INNS Awards:

2011 **Hebb Award** goes to: Paul Werbos

2011 **Helmholtz Award** goes to: Jack Cowan

2011 **Gabor Award** goes to: Robert Kozma

2011 **INNS Young Investigator Awards** go to:
Damien Coyle and Weifeng Liu

These awards were decided after careful deliberations by the Awards Committee and the Board of Governors.

Paul Werbos, the Hebb Award recipient, is recognized for his long-standing contribution and achievements in biological and computational learning.

Jack Cowan, the Helmholtz Award recipient, is recognized for his many years of contribution and achievements in understanding sensation/perception.

Robert Kozma, the Gabor Award recipient, is recognized for his achievements in engineering/ application of neural networks.

Damien Coyle and Weifeng Liu, the Young Investigator Award recipients, are recognized for significant contributions in the field of Neural Networks by a young person (with no more than five years postdoctoral experience and who are under forty years of age).

These awards were presented at IJCNN 2011 in San Jose. ■

New Senior Members

By Irwin King
VP for Membership, INNS

Petia Georgieva, U. Aveiro, Portugal

Yoshifusa Ito, Aichi Medical University, Japan

Richard Neville, U. Manchester, UK

Carme Torras Genis, Spanish Council of Scientific Research (CSIC), Spain

Marc Van Hulle, K.U. Leuven, Belgium

Zeng-Guang Hou, Chinese Academy of Sciences, China

Hava Siegelmann, UMass Amherst, USA,

Let's congratulation the new Senior Members.

Clockwise from the top: Professors Georgieva, Neville, Genis, Hull, Hou, and Siegelmann.

Autonomous Machine Learning (AML) Section

By Asim Roy
Arizona State University
www.lifeboat.com/ex/bios.asim.roy

I am pleased to announce that Autonomous Machine Learning (AML) SIG is the first SIG to be elevated to a Section within INNS. Being a Section has the following benefits:

- an option to charge a due for the section (AML Section dues will be $25)
- a special track on AML during IJCNN (when organized by INNS)
- a special issue/section in the new INNS magazine "Natural Intelligence."

Being a Section also comes with additional obligations as specified by the BOG:

- actively promoting neural networks and the Section's special focus and topics
- actively recruiting new (paying) members to INNS
- maintaining a high professional and academic standard in the Section activities; becoming a prestigious organization in the field

We currently have a number of volunteers helping out with AML Section affairs, most notably Prof. Nistor Grozavu of Institut Galilée, Paris 13 University, France, and Prof. Nils T Siebel of HTW University of Applied Sciences Berlin, Germany. But we need to get better organized and create a committee to handle our expanded set of activities. Please let me know (asim.roy@asu.edu) if you want to volunteer for next year (2012). We can have elections next year (2012) once INNS members sign up for the AML Section. Again, we hope more INNS members will join the AML Section this year and be part of the worldwide effort to create widely deployable learning systems.

Motivation for AML Section

Much of the justification for creating this SIG (now a Section) is derived from the report of a US National Science Foundation (NSF) workshop in July, 2007 on "Future Challenges for the Science and Engineering of Learning." Here is the summary of the "Open Questions in Both Biological and Machine Learning" from the workshop (<http://www.cnl.salk.edu/Media/NSFWorkshopReport.v4.pdf>).

"Biological learners have the ability to learn autonomously, in an ever changing and uncertain world. This property includes the ability to generate their own supervision, select the most informative training samples, produce their own loss function, and evaluate their own performance. More importantly, it appears that biological learners can effectively produce appropriate internal representations for composable percepts -- a kind of organizational scaffold - - as part of the learning process. By contrast, virtually all current approaches to machine learning typically require a human supervisor to design the learning architecture, select the training examples, design the form of the representation of the training examples, choose the learning algorithm, set the learning parameters, decide when to stop learning, and choose the way in which the performance of the learning algorithm is evaluated. This strong dependence on human supervision is greatly retarding the development and ubiquitous deployment autonomous artificial learning systems. Although we are beginning to understand some of the learning systems used by brains, many aspects of autonomous learning have not yet been identified."

We thought INNS and the neural network community at large has a special obligation to step up to this challenge of creating autonomous learning systems that do not depend on human supervision. INNS approved the formation of AML SIG in April 2009 and our membership has grown since then. Our current mailing list has more than 225 members worldwide and its growing.

AML Section objectives

The objectives of this Section are to:

- •promote research and development of autonomous machine learning systems;
- •create a body of researchers focused on autonomous learning systems;
- •facilitate collaboration among researchers on this new breed of learning algorithms;
- •organize special sessions on autonomous machine learning at various conferences (IJCNN, WCCI and others);
- •organize special workshops at various conferences to get a deeper understanding of autonomous learning by biological systems; invite prominent researchers to these workshops;
- •promote applications of autonomous machine learning systems in various application areas;

We hope more INNS members will join the AML Section this year and be part of the worldwide effort to create widely deployable learning systems.

AML Section Website

We currently have a website http://autonomoussystems.org/default.html that is maintained by Prof. Nistor Grozavu of Institut Galilée, Paris 13 University, France. We would like to expand this website to post information about various research activities of our members, job openings, papers and other special events.

AML Section mail-server

The mail-server for the AML SIG (now a Section) and its various specialized discussion lists is maintained by Prof. Nils T Siebel of HTW University of Applied Sciences Berlin, Germany. You can subscribe and unsubscribe to/from the AML SIG mailing list through the website http://erlars.org/mailman/listinfo/aml-sig_erlars.org. If you want to post to everyone all you need to do is send an email to aml-sig@erlars.org. Messages are moderated to keep the number of messages and their relevancy to the list subject in check.

AML Section discussion groups

One discussion this summer was about newly discovered concept cells in the human brain and it continued for nearly two months. The concept cells were discovered by of a group of neuroscientists at UCLA (University of California, Los Angeles, USA) under the leadership of Prof. Itzhak Fried and Caltech (California Institute of Technology, Pasadena, CA, USA) under the leadership of Prof. Christof Koch. Participants in this discussion included Profs. Fried and Koch and their co-authors. There is an article titled "Discovery of concept cells in the human brain – Could it change our science?" in this first issue of Natural Intelligence. We invited Dr. Moran Cerf from the UCLA/Caltech group to give a talk on concept cells and the various experiments with epilepsy patients at our AML SIG annual meeting in San Jose during IJCNN 2011. It turned out to be one of the most interesting and informative talks at IJCCN 2011.

These discussions have indeed been very productive in clarifying theoretical issues and ideas. So we hope to continue discussions of this nature within our mailing list. And we try to bring the best experts in the field to join these discussions. So this could turn out to be of tremendous help to the challenging research we are engaged in.

AML Section Committee

We currently have a number of volunteers helping out with AML Section affairs, most notably Prof. Nistor Grozavu of Institut Galilée, Paris 13 University, France, and Prof. Nils T Siebel of HTW University of Applied Sciences Berlin, Germany. But we need to get better organized and create a committee to handle our expanded set of activities. We have got some volunteers. But please let me know (asim.roy@asu.edu) if you want to volunteer for next year (2012). We can have elections next year (2012) once INNS members sign up for the AML Section. Again, we hope more INNS members will join the AML Section this year and be part of the worldwide effort to create widely deployable learning systems.

AML Sessions, panels and workshops at conferences

So far, we have been fairly active in organizing sessions at IJCNNs. We organized 7 special sessions and 2 panel discussions in the Autonomous Machine Learning track at WCCI 2010 in Barcelona. Also, we organized 7 special sessions, 2 panel discussions and a workshop in the AML track at IJCNN2011 in San Jose. ■

Spiking Neural Networks SIG

By Narayan Srinivasa
HRL Laboratories

Spiking neural networks are presently a hot topic in neural network research. Spiking models have been receiving an increasing amount of attention, both due to their computational power and bio plausibility. Added to this is the research and development in Neuromorphic Engineering, which aims to create networks of spiking neurons and learning synapses in hardware. Both the EU and NSF fund the annual Neuromorphic Engineering workshop, held in Italy and Colorado.

There have been numerous models of SNN proposed. These vary in biological realism, hardware realization and applications. However, there is still much to explore, in terms of models, architectures, learning and implementation. Looming over all these are issues such as computational complexity and the question of how cognition can be realized through the synergistic interaction within and between networks of spiking neurons.

Many of the challenges associated with spiking neuron research spans a multidisciplinary research domain encompassing Neuroscience, Computer Science, Mathematics, and various others. The nature of these challenges is further augmented because of the lack of cross talk between the various interested communities. The problem is further exacerbated by diverging research priorities that place different levels of emphasis on different types of results. This is an issue that has only recently been realized. The urgency of resolution of the issue is therefore paramount and will lead to the large positive step in the development of spiking neuron based cognitive systems.

INNS (International Neural Network Society) and the neural network community at large has a special obligation to step up to this challenge of creating a community of researchers interested in setting up a collaboration platform between Neuroscientists, Computer Scientists, Mathematicians, and related research communities to further the understanding of spiking neurons and networks, and thereby advance cognitive systems research.. Hence we are proposing to INNS that we form a SIG (Special Interest Group) on Spiking neural networks. We are also planning to organize a special session on "Modeling cognitive systems using spiking neurons" for IJCNN 2012.

The objectives of this SIG will be to:

- promote research and development of spiking neuron models and networks
- create a body of researchers from Neuroscience, Computer Science, Mathematics, and related fields to facilitate crosstalk between the disciplines
- facilitate collaboration among researchers on these models;
- encourage the formation of joint multidisciplinary research objectives for spiking models;
- organizing sessions on at various conferences (IJCNN, WCCI and others) on spiking neuron and network

models and the realization of cognitive systems using these models;
- •promote applications of spiking neural networks in various application areas;

Initial list of INNS members participating in this SIG

Paolo Arena, Università degli Studi di Catania, Italy
Barry Bentley, University of Cambridge, UK
Thomas Caudell, Univ. of New Mexico, USA
Mark Cavanagh, Uni. of South Florida, USA
Sergio Davies, Univ. of Manchester, UK
Harry Erwin, University of Sunderland, UK
Erol Gelenbe, Imperial College, UK
Michael Healy, Univ. of New Mexico, USA
Christof Koch, Caltech, USA
David Lester, University of Manchester, UK
Francesco Carlo Morabito, University Mediterranea of Reggio Calabria, Italy
Dragan Nikolik, Maastricht School of Management, Netherlands
David Olmsted, Independent Consultant, UK
Steve Potter, Georgia Institute of Technology and Emory University, USA
Rodrigo Quian Quiroga, Univ. of Liecester, UK
Kiruthika Ramanathan, Data Storage Institute, Singapore
Alexander Rast, University of Manchester, UK
Asim Roy, Arizona State University, USA
Fredrik Sandin, Lule°a University of Technology, Sweden
Heike Sichtig, University of Florida, USA
Narayan Srinivasa, HRL Laboratories, CA, USA
John Weng, Michigan State University, USA
Hava Siegelmann, University of Massachusetts, Amherst, USA
Dragan A. Nikolik, Maastricht School of Management (MSM), the Netherlands ■

2011 International Joint Conference on Neural Networks (IJCNN 2011)

By Ali A. Minai, General Chair – IJCNN 2011
University of Cincinnati

The 2011 International Joint Conference on Neural Networks (IJCNN 2011) was held in San Jose, California, from July 31 to August 5, continuing the tradition of joint sponsorship by the International Neural Network Society (INNS) and the IEEE Computational Intelligence Society (IEEE-CIS). As in past years, this was a very successful conference, for which the leadership of both organizations, and particularly the Presidents, Ron Sun and Gary Yen, deserve great credit.

This fusion of biology and engineering was the key theme of IJCNN 2011, and featured prominently in many aspects of the conference – most notably in a special day-long symposium called “From Brains to Machines”, organized with generous sponsorship from the National Science Foundation (NSF). This symposium featured plenary talks by Michael Arbib on “Brains, Machines, and Buildings” and Dharmendra Modha on “Cognitive Computing: Neuroscience, Supercomputing and Nanotechnology”, as well as invited presentations by Adam Gazzaley, Cheryl Grady, Jennie Si, Vinod Menon, Jose Carmena, Michel Maharbiz, Theodore Berger and Dileep George, all of whom are leaders in the areas of brain networks, brain-machine interfaces and neuromorphic systems. The organization of the symposium was led by Steve Bressler, the Special Sessions Chair for IJCNN 2011.

In addition to this keynote symposium, other plenary talks by Stefan Schaal, Juergen Schmidhuber, Leon Glass and Andrew Ng also reflected the broad themes of cognition and intelligence, moving beyond traditional neural networks into areas like embodied robotics, data mining, cognition and creativity. This series culminated in a featured plenary session entitled “The Emergence of Mind” with talks by Walter Freeman, Stephen Grossberg and Bernard Baars. The theme of the conference was also reinforced by extended tracks of invited and contributed talks and panels on neuromorphic systems (organized by Robert Kozma and Robinson Pino), autonomous intelligent systems (organized by Asim Roy and John Weng), and smart grid technologies (organized by Danilo Mandic, Ganesh K. Venayagamoorthy and Lingfeng Wang). The conference also featured 19 tutorials organized under the leadership of the Tutorials Chair, Robert Kozma, as well as 8 workshops (6 half-day and 2 full day) whose organization was supervised by Robi Polikar, the Workshops Chair. These tutorials and workshops also covered a broad range of themes and topics. All in all, this was probably one of the most interdisciplinary IJCNNs in recent times.

A very special, though somber, event at IJCNN 2011 was a special plenary session convened to remember one of the pioneers in the field of neural networks, David Rumelhart, who passed away in March 2011. The session, which was organized by the Program Chair, Hava Siegelmann, included remembrances by colleagues, friends and family, and a technical talk by Michael Jordan who worked with David Rumelhart in the 1990s. This memorable session was, indeed a highlight of IJCNN 2011, and will be in the minds of those who attended.

This year’s IJCNN also tried a new experiment, allowing authors in the areas of neuroscience and neurocognition to submit abstracts rather than full papers. This was done to encourage submissions from research communities where writing full-length papers for conferences is not standard practice. The experiment was successful in that 85 abstracts were submitted to the conference, of which 53 (64%) were included in the final program. IJCNN 2011 also received 620 full papers, of which 468 (75%) were accepted for presentation. The conference program included 337 oral presentations (including plenary talks) and 194 poster presentations.

The successful organization of IJCNN 2011 owed a lot to the stalwart work of the Program Chair, Hava Siegelmann, and the two Program Co-Chairs, Michael Georgeopoulos and Cesare Alippi, as well as all the other members of the Organizing Committee. In particular, Marios Polycarpou (Publications Chair), Georgios Anagnostopoulos (Registra-

Panel discussion during the NSF-sponsored symposium "From Brains to Machines" – L to R: Steven Bressler, Jennie Si, Vinod Menon, Cheryl Grady, Adam Gazzaley. (Photo: Wlodzislaw Duch)

David E. Rumelhart Memorial Session – L to R: Michael Jordan, Adele Abrahamsen, Karl Rumelhart (son), Marilyn Austin (former wife), Robert Glushko (founder of the Rumelhart Prize). (photo: Ali Minai)

tion Chair), Robert Kozma (Tutorials Chair), Robi Polikar (Workshops Chair), Simona Doboli (Panels Chair), Risto Miikkulainen (Plenary Chair) and Tom Cholewo (Web Reviews Chair) all put in a special effort towards the meeting's success. Steve Bressler, the Special Sessions Chair, did truly heroic work in helping obtain NSF funding and putting together the "From Brains to Machines" symposium. A wonderful set of competitions was organized by the Competition Chairs, Sven Crone and Isabelle Guyon. Several members of the Organizing Committee – notably Irwin King, Yoonsuck Choe, Haibo He and Manuel Roveri – worked very hard to actively publicize the conference in various forums, and the conference received strong support from the INNS Board of Governors – especially Ron Sun (President), Nikola Kasabov (Past President), Danil Prokhorov (Vice-President for Conferences), David Casasent (Treasurer) and DeLiang Wang. The Program Committee and a large group of dedicated reviewers helped IJCNN 2011 maintain the high standards of previous meetings. The professional work put in by the team from Rees Management Group led by Jane Shepard was also instrumental in the successful organization of the conference.

In addition to the proceedings, IJCNN 2011 also generated other useful multimedia. The IEEE CIS VP for Education, Jennie Si, organized the recording of all plenary talks, which will be available through the IEEE Computational Intelligence Society. All talks in the "From Brains to Machines" symposium were also recorded, and will be made available to the public. A special issue of Neural Networks with expanded versions of selected IJCNN papers will be published in mid-2012, edited by

Panel discussion during the NSF-sponsored symposium "From Brains to Machines" – L to R: Steven Bressler, Dileep George, Michel Maharbiz, Jose Carmena, Theodore Berger (photo: Wlodzislaw Duch)

Jean-Philippe Thivierge and the members of the IJCNN 2011 Executive Committee.

Three decades ago, the computer revolution took root and flourished in the fertile soil of what came to be known as Silicon Valley. It is appropriate that those who are igniting another technological revolution to create truly life-like intelligence assembled in the heart of Silicon Valley once again to exchange ideas and celebrate the future. It was a great honor for me to be a part of this exciting event. I am sure that IJCNN 2011 will be the prelude to greater growth and success for the entire field of neural networks. ■

[Note: *This report is being published simultaneously in the International Neural Network Society Magazine and the IEEE Computational Intelligence Magazine.*]

Regional SIG – Italy and Italian Society of Neural Networks (SIREN) WIRN workshop

By Francesco Carlo Morabito, Regional Chair
University Mediterranea of Reggio Calabria

Neural Network researches are alive and continuously pervade novel fields! This is the final message from the Italian Society of Neural Networks (SIREN) WIRN workshop (co-sponsored by International Neural Network Society and in co-operation with the regional Italian Special Interest, Group, founded in 1997). The Italy SIG is chaired by prof. Morabito and was originally proposed by Prof. Harold Szu. About 50 participants attended the meeting that took place, as usual, for the 21st year, in Vietri Sul Mare (Italy). There, in 1988, Professor Eduardo Renato Caianiello, died in 1993, founded the Society which is logistically located within the International Institute of Advanced Scientific Studies (IIASS), in a splendid place on the Peninsula Sorrentina beach.

The conference is organized continuously, since 1989, and it is a traditional event devoted to the discussion of novelties and innovations related to Artificial Neural Networks and Natural Intelligence. Along this vein, this year, some researchers from apparently such different fields like botany and philosophy proposed novel truly interesting methodologies that can favour our endeavour of introducing novel ideas in neural algorithms and machine learning. In particular, mechanisms of signalling and communication in

A group of WIRN-SIREN attendees among which Prof. Boncinelli, Morabito, Esposito, Maldonato, and Palmieri.

The "Neuromorphic Engineering" group in Vietri S/M (A. Uncini, P. Motto-Ros, E. Chicca, B.Apolloni, F.C. Morabito, G. Indiveri).

plants may be interpreted as forms of "intelligence" somehow remembering learning and adaptation.

The 21st edition of WIRN featured three special sessions: *Models of Behaviours for Human-Machine Interaction* (Chairs: A. Esposito, M. Maldonato, L. Trojano); *Autonomous Machine Learning* (Chairs: A. Roy, P. Arena), in cooperation with INNS SIG AML, and *Neuromorphic Engineering* (Chairs: E. Chicca, E. Pasero), with excellent talks from the invited speakers, Asim Roy ("A theory of the brain"), Bruno Apolloni ("Training a network of mobile neurons"), M. Frasca and L. Fortuna ("Inside Cellular Nonlinear Neural Networks Dynamics: Arts, Complexity and Time"), Giacomo Indiveri ("Neuromorphic processors: event-based VLSI models of cortical circuits for brain-inspired computation"), Prof. Edoardo Boncinelli ("Conscience's problems"), author of several excellent best-selling scientific books, and M. Maldonado ("Embodied mind. Prolegomena for a neuro-phenomenological theory").

During the workshop, there was a meeting of the INNS SIG on Autonomous Machine Learning, chaired by Asim Roy, that was also useful to delineate the lines of interactions between the Italian community and the novel SIG. Also, since the presentation of Prof. Lester on Spiking Neural Networks, it was thought to propose a novel SIG on such fascinating field particularly relevant also from the Electronic Engineering perspective.

The traditional E. R. Caianiello Award for the best Italian Ph.D. Thesis on Neural Network was presented to an Italian researcher, dr. Francesco Iorio, which was selected among several excellent participants. He is now EMBL European Bioinformatics Institute & Wellcome Trust Sanger Institute Post-Doctoral (ESPOD) Fellow with the Systems Biomedicine Group, EMBL-EBI, Wellcome Trust Genome Campus of Cambridge, UK. The thesis concerned a novel aspect of the emergent behaviour of dynamic networks ("complex networks") applied to the genomics and the study of novel effective drugs by exploiting some network relationships among proteins. The prize was sponsored by the international firm Aubay SpA.

During the workshop, the novel Steering Committee of the Italian Society of Neural Networks was elected, and Prof. Morabito was re-elected as President of SIREN. ■

Regional SIG – India and National Symposium on Where is Intelligent Computing (SWIC'11)

By Suash Deb
C.V. Raman College of Engineering

National Symposium on Where is Intelligent Computing (SWIC'11) was organized (9th Sept'11) jointly by the Electronics & Telecommunication Engineering Department of C.V. Raman College of Engineering (CVRCE), Bhubaneswar & the International Neural Network Society (INNS) India Regional Chapter, popularly known as INNS-India. It is the first INNS event in the entire eastern India & hence the significance. The event commenced with a nice inspiring speech as sent by the INNS President, Dr. Ron Sun. He outlined the scope of INNS & appraised the participants about the INNS-India being recently named as the Most Active Regional Chapter of INNS by the Board-of-Governors of INNS.

The dignitaries include eminent people from India & abroad, including the Honorable Vice Chancellor of Sambalpur University - Prof. Arun K. Pujari, Dean of IIT Bhubaneswar – Prof. Ganapati Panda, Director of Global Education Centre, Infosys ltd, Mysore – Dr. B. M. Subraya, Senior Faculty of Iwate Prefectural University, Japan – Prof. Basabi Chakraborty. Apart from them, invited speeches were delivered by Dr. Mahua Bhattacharya (Indian Inst. of IT & Management, Gwalior), Dr. Alok K. Deb (IIT, Kharagpur) & Dr. Babita Majhi (S 'O' A University, Bhubaneswar). Each of them deliberated on various issues related to the failure of the scientific community to gift the human beings with intelligent computers.

Inauguration ceremony of SWIC'11

Lighting of lamp and seeking divine blessings for the success of the event at the start of the inauguration

SWIC'11 received an overwhelming response for participation & ultimately could accommodate a total of 70 odd registered participants (including 10 from CVRCE). Prof. Suash Deb, President of INNS India Regional Chapter was the Chair & Dr. P. Kanungo, Head-of-the-Department of the Dept. of ETC, C.V. Raman College of Engineering had been the convener of SWIC'11. ■

CIBB 2011, 8th INTERNATIONAL MEETING ON COMPUTATIONAL INTELLIGENCE METHODS FOR BIOINFORMATICS AND BIOSTATISTICS

Palazzo Feltrinelli, Gargnano, Lago di Garda (Italy), June 30-July 2, 2011
http://www.neuronelab.dmi.unisa.it/cibb2011

By Elia Mario Biganzoli,Chair of CIBB 2011
University of Milano, Italy

The CIBB 2011, International Meeting on Computational Intelligence Methods for Bioinformatics and Biostatistics (http://www.neuronelab.dmi.unisa.it/cibb2011) has been held at the beautiful villa Palazzo Feltrinelli directly on Lago di Garda in Gargnano (Italy) on June 30-July 2 2011, chaired by Elia Biganzoli, Andrea Tettamanzi (University of Milano, Italy), Alfredo Vellido (Universitat Politècnica de Catalunya, Barcelona, Spain). It is has been the eighth of a series of workshops aimed to provide a forum open to researchers from different disciplines to present and discuss problems concerning computational techniques in Bioinformatics, Medical Informatics, Systems Biology and Biostatistics with a particular focus on computation learning and flexible statistical methods as Neural Networks, Machine Learning, Fuzzy Logic, and Evolutionary Computation approaches. The CIBB meetings series is organized yearly from 2004, and from 2006 it has been the main event sponsored by the Special Interest Group on Bioinformatics of the International Neural Network Society (INNS). The 8th CIBB meeting in Gargnano, has been a joint operation of the Special Interest Groups on Bioinformatics and Biopattern of INNS and of the Task Force on Neural Networks of the IEEE CIS Technical Committee on Bioinformatics and Bioengineering with the sponsorship and endorsement of university and research institutions and international statistical software companies.

The conference was opened by a welcome messages from Professor Jon Garibaldi, Nottingham University, UK as special guest for the 150th anniversary of unification of Italy: The meeting included 31 presentations, four special sessions, the plenary talks of Nikola Kasabov (Auckland University of Technology, New Zeland), Elena Marchiori (Radboud University, Heyendaalseweg, The Netherlands), and Clelia Di Serio, (Vita-Salute San Raffaele University, Milano, Italy) and a tutorial by Francesco Masulli (University of Genova, Italy).

The program of CIBB 2009 allowed to the 50 participants to compare many high level scientific interdisciplinary experiences in the field of development of computational intelligence models and of their biomedical and bioinformatics applications. Moreover, a panel including Elia Biganzoli, Francesco Masulli, Leif Peterson (Center for Biostatistics, TMHR, Houston, TX, USA) and Roberto Tagliaferri (University of Salerno, Italy), discussed the present collaboration in bioinformatics and biostatistics between INNS and IEEE-CIS and the next joint initiatives with the announcement of the next CIBB 2012 Meeting to be held at The Methodist Hospital, Houston TX, USA. ■

Professor Nikola Kasabov assigns the Best Student Paper Awards to Davide Chicco.

CIBB 2011 participants in the beautiful garden of Palazzo Feltrinelli.

Call for Papers

Neural Networks Special Issue: *Autonomous Learning*

Guest editors:

Asim Roy, *Arizona State University, USA (asim.roy@asu.edu) (Lead guest editor)*
John Taylor, *King's College London, UK (john.g.taylor@kcl.ac.uk)*
Bruno Apolloni, *University of Milan, Italy (apolloni@dsi.unimi.it)*
Leonid Perlovsky, *Harvard University and The Air Force Research Laboratory, USA (leonid@seas.harvard.edu)*
Ali Minai, *University of Cincinnati, USA (minaiaa@gmail.com)*

Autonomous learning is a very broad term and includes many different kinds of learning. Fundamental to all of them is some kind of a learning algorithm. Whatever the kind of learning, we generally have not been able to deploy the learning systems on a very wide scale, although there certainly are exceptions.

One of the biggest challenges to wider deployment of existing learning systems comes from algorithmic control. Most of the current learning algorithms require parameters to be set individually for almost every problem to be solved. The limitations of the current learning systems, compared to biological ones, was pointed out in a 2007 National Science Foundation (USA) report ((<http://www.cnl.salk.edu/Media/NSFWorkshopReport.v4.pdf). Here's a part of the summary of that report:

"Biological learners have the ability to learn autonomously, in an ever changing and uncertain world. This property includes the ability to generate their own supervision, select the most informative training samples, produce their own loss function, and evaluate their own performance. More importantly, it appears that biological learners can effectively produce appropriate internal representations for composable percepts -- a kind of organizational scaffold - - as part of the learning process. By contrast, virtually all current approaches to machine learning typically require a human supervisor to design the learning architecture, select the training examples, design the form of the representation of the training examples, choose the learning algorithm, set the learning parameters, decide when to stop learning, and choose the way in which the performance of the learning algorithm is evaluated. This strong dependence on human supervision is greatly retarding the development and ubiquitous deployment autonomous artificial learning systems."

This special issue of *Neural Networks* will be on the topic of autonomous learning, focusing mainly on automation of learning methods that can avoid the kinds of dependencies highlighted in the NSF report. We invite original and unpublished research contributions on algorithms for any type of learning problem.

Topics of interest include – but are not limited to:

- Unsupervised learning systems;
- Autonomous learning of reasoning;
- Autonomous learning of motor control;
- Autonomous control systems and free will;
- Autonomous robotic systems;
- Autonomy as based on internal reward and value systems and their learning and development;
- Autonomous systems and the human situation
- Emergent models of perception, cognition and action
- Emergent cognitive architectures
- Developmental and embodied models of learning

Prospective authors should visit http://ees.elsevier.com/neunet/ for information on paper submission. On the first page of the manuscript as well as on the cover letter, indicate clearly that the manuscript is submitted to the *Neural Networks Special Issue: Autonomous Learning*. Manuscripts will be peer reviewed using *Neural Networks* guidelines.

Manuscript submission due:	January 1, 2012
First review completed:	April 1, 2012
Revised manuscript due:	June 1, 2012
Second review completed, final decisions to authors:	July 1, 2012
Final manuscript due:	August 1, 2012 ■

Neural Networks Special Issue: *Neuromorphic Engineering: from Neural Systems to Brain-Like Engineered Systems*

Co-Editors

Andreas Andreou, *John Hopkins University, USA*
Elisabetta Chicca, *Bielefeld University, Germany*
David Lester, *University of Manchester, UK*
Francesco Carlo Morabito*, *University Mediterranea Reggio Calabria, Italy*

* *Corresponding Editor*
Address for early submission of proposals:
Professor Francesco Carlo Morabito
University Mediterranea
DIMET Department
E-mail address: morabito@unirc.it

Submission information

Deadline for submission:	May 31, 2012
Notification of acceptance:	July 31, 2012
Publication:	Early 2013

Format: as for normal papers in the journal (no longer than 10,000 words). Prospective authors should visit http://ees.elsevier.com/neunet/ for information on paper submission

The styles of computation used by biological systems are fundamentally different from those used by conventional computers: biological neural networks process information using energy-efficient asynchronous, event-driven, methods. They are adaptive, fault-tolerant, self-repairing, learn from their interactions with the environment, and can flexibly produce complex behaviors by combining multiple instances of simpler elements. These biological abilities yield a potentially attractive alternative to conventional computing strategies. A special focus of this issue is Neuromorphic VLSI systems that are composed of Very Large Scale Integrated (VLSI) devices with hybrid analog/digital circuits that implement hardware models of biological systems. When implemented in VLSI (including FPGA) technology, neuromorphic systems often have similar strategies for maximizing compactness, optimizing robustness to noise, minimizing power consumption, and increasing fault tolerance. By emulating the neural style of computation, neuromorphic VLSI architectures can exploit to the fullest potential the features of advanced scaled VLSI processes and future emerging technologies, naturally coping with the problems that characterize them, such as device inhomogeneities, and mismatch.

In this Special Issue we call for a broad range of papers on Neuromorphic Engineering. The various contributions will describe recent developments and progress in understanding the interplay between biology and technology for the developments of bio-inspired systems that reproduce functionality and rapid processing of their biological counterpart.

This Special Issue seeks to explore the possible synergies and interactions of different perspectives.

Suggested topics of interest include, but are not limited to, the following research and application areas:

- Neuromorphic spike-based neural processing systems
- Neuromorphic event-driven sensory systems
- Neuromorphic autonomous systems for robotic applications
- Neuromorphic real-time behaving systems
- Circuits and systems for large scale neural networks
- Neuromorphic auditory processing systems
- Plasticity and learning in neuromorphic systems
- Memristors-based Neural Circuits
- System-level brain-like processing ■

IEEE Trans. Autonomous Mental Development Special Issue:

Biologically-Inspired Human-Robot Interactions

http://research.microsoft.com/~zhang/IEEE-TAMD/CFP-SI-HRI.html

Co-Editors:

Frederick C Harris, Jr., *University of Nevada (fredh@cse.unr.edu)*

Jeffrey Krichmar, *University of California (jkrichma@uci.edu)*

Hava Siegelmann, *University of Massachusetts Amherst (hava@cs.umass.edu)*

Hiroaki Wagatsuma, *Kyushu Institute of Technology, (waga@brain.kyutech.ac.jp)*

As robots become more common in our daily activities, human-robot interactions and human-computer interfaces are becoming increasingly important. Despite considerable progress in this relatively new field, very few researchers have paid attention to how the brain, cognition, and underlying biological mechanisms are involved in such interactions.

This call requests papers that bring together fields of study, such as cognitive architectures, computational neuroscience, developmental psychology, machine psychology, and socially affective robotics, to advance the field of human-robot interaction. A robot that shares many of the attributes of the human it is interacting with would not only result in a more sophisticated robot, but it may also cause the human to respond more naturally, and be more willing to cooperate with such a robot.

Submitted papers should further the field of Human-Robot Interaction through biologically inspired algorithms or methods. Topics may include, but are not limited to:

- Brain imaging during human-robot interaction
- Cooperative behavior and/or teamwork with robots and humans
- Emotion and empathy in robotic systems
- Gesture recognition using neural systems
- Human brain activity while interacting with robotic systems
- Human and robot shared or joint attention
- Natural language communication
- Natural vision systems
- Robot imitation of human behavior
- Socially affective robots
- Social cognition
- Space sharing and co-existence between humans and machines
- Theory of mind in robots

Two kinds of submissions are possible:

- Regular papers, up to 15 double column pages.
- Correspondence papers either presenting a "perspective" that includes insights into issues of wider scope than a regular paper but without being highly computational in style or presenting concise description of recent technical results, up to 8 double column pages.

<u>*Instructions for authors:*</u>
http://ieee-cis.org/pubs/tamd/authors/

We are accepting submissions through Manuscript Central at http://mc.manuscriptcentral.com/tamd-ieee (please select « Bio-inspired human robot interaction » as the submission type)

When submitting your manuscript, please also cc jkrichma@uci.edu, fredh@cse.unr.edu, hava@cs.umass.edu, and waga@brain.kyutech.ac.jp.

Timeline:
December 31, 2011 – Deadline for paper submission February 15, 2012 – Notification April 15, 2012 – Final version May 1, 2012 – Electronic publication June 15, 2012 – Printed publication. ■

IEEE Communications Magazine Special Issue: *Information-Centric Networking*

Feature Topic Editors

Dr. Kostas Pentikousis, *Huawei Technologies European Research Centre*
Email: k.pentikousis@huawei.com
Dr. Prosper Chemouil, *Orange Labs*
Email: prosper.chemouil@orange-ftgroup.com
Dr. Kathleen Nichols, *Pollere Inc*
Email: nichols@pollere.net
Prof. George Pavlou, *University College London, Dept. of Electronic & Electrical Engineering*
Email: g.pavlou@ee.ucl.ac.uk
Prof. Dan Massey, *Colorado State University*
Email: massey@cs.colostate.edu

Information-Centric Networking (ICN) marks a fundamental shift in communications and networking. ICN focuses on finding and transmitting information to end users instead of connecting end hosts that exchange information. The key concepts are expected to have a huge impact on the familiar textbook protocol stack, in network architecture in general, and will create new opportunities for all associated stakeholders including equipment vendors, network operators, service and content providers, and above all end-users.

Scope and Objectives
Information-centric networking is to succeed only if it can to provide clearly superior solutions to well-known problems in the current generation of all-IP networks and can be introduced to general usage incrementally. We invite authors to consider the following aspects with respect to information-centric networks:
- Naming & addressing: What breakthroughs in naming and addressing will make ICN scalable when faced with a global network of billions of devices and zettabytes of available content?
- Protocol stack: Can ICN deliver a neat and simple protocol stack?
- Network architecture: What does a ICN network architecture look like?
- Management: What are the essential characteristics of a complete management framework that is scalable, flexible, and suitable for ICN?
- Caching: New issues to be addressed such as buffer management and caching policy.
- Energy efficiency: Will ICN pave the way to a holistic energy efficient operation?
- Internet of Things (IoT): How does ICN scale in the scenarios envisioned for the IoT and how does it compare with current IP-based IoT solutions?
- Security: Can ICN foster the development of a more secure and trusted global communications infrastructure?
- Which business models could foster a fair relationship between content producers, content providers and service/network providers?

Submitted articles do not need to cover all these aspects but should strive to clearly contrast the ICN approach with the current TCP/IP-based state of affairs. Prospective authors should describe the key concepts, design, implementation, and evaluation of ICN proposals.
Articles that demonstrate the feasibility of groundbreaking approaches through testbed/experimental results are particularly welcome. We invite authors to submit articles reporting original, previously unpublished research work on information-centric networking. Authors can find article guidelines at http://dl.comsoc.org/ci1/info/cfp/cfpcommag0712.htm.

Submission Schedule
- Submission Deadline: November 1, 2011
- Notification of Acceptance: February 29, 2012
- Final Manuscript Due: May 1, 2012
- Publication Date: July 2012 ■

ESANN 2012 *** *20th anniversary !* ***
20th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning
April 25-26-27, 2012, Bruges, Belgium
http://www.esann.org

Deadline for submission of papers: November 30, 2011

Topics:
Machine learning, artificial neural networks, computational intelligence and related topics (see below for a more detailed description of the conference topics).

Special sessions:
(see http://www.esann.org for abstracts):

- *Recent developments in clustering algorithms*
Charles Bouveyron, Université Paris 1 (France), Barbara Hammer, Bielefeld University (Germany), Thomas Villmann, University of Applied Sciences Mittweida (Germany)

- *Theory and Practice of Adaptive Input Driven Dynamical Systems*
Peter Tino, The University of Birmingham (UK), Jochen Steil, Bielefeld University (Germany)

- *Interpretable models in machine learning*
Paulo Lisboa, Liverpool John Moores University (UK), Alfredo Vellido, Technical University of Catalonia (Spain), José D. Martín, University of Valencia (Spain)

- *Parallel hardware architectures for acceleration of neural network computation*
Ulrich Rückert, Bielefeld University (Germany), Erzsébet Merényi, Rice University (USA)

• *Machine Ensembles: Theory and Applications*
Anibal R. Figueiras-Vidal, Universidad Carlos III de Madrid (Spain), Lior Rokach, Department of Information Systems Engineering, Ben-Gurion University of the Negev (Israel)

• *Statistical methods and kernel-based algorithms*
Kris De Brabanter, Katholieke Universiteit Leuven (Belgium)

Scope and topics:

Since its first happening in 1993, the European Symposium on Artificial Neural Networks has become the reference for researchers on fundamentals and theoretical aspects of artificial neural networks, computational intelligence, machine learning and related topics. Each year, around 100 specialists attend ESANN, in order to present their latest results and comprehensive surveys, and to discuss the future developments in this field.

The ESANN 2012 conference will follow this tradition, while adapting its scope to the recent developments in the field. The ESANN conferences cover artificial neural networks, machine learning, statistical information processing and computational intelligence. Mathematical foundations, algorithms and tools, and applications are covered.

The following is a non-exhaustive list of machine learning, computational intelligence and artificial neural networks topics covered during the ESANN conferences:

THEORY and MODELS

Statistical and mathematical aspects of learning
Feedforward models
Kernel machines
Graphical models, EM and Bayesian learning
Vector quantization and self-organizing maps
Recurrent networks and dynamical systems
Blind signal processing
Ensemble learning
Nonlinear projection and data visualization
Fuzzy neural networks
Evolutionary computation
Bio-inspired systems

INFORMATION PROCESSING and APPLICATIONS

Data mining
Signal processing and modeling
Approximation and identification
Classification and clustering
Feature extraction and dimension reduction
Time series forecasting
Multimodal interfaces and multichannel processing
Adaptive control
Vision and sensory systems
Biometry
Bioinformatics
Brain-computer interfaces
Neuroinformatics

Papers will be presented orally (single track) and in poster sessions; all posters will be complemented by a short oral presentation during a plenary session. It is important to mention that the topics of a paper decide if it better fits into an oral or a poster session, not its quality. The selection of posters will be identical to oral presentations, and both will be printed in the same way in the proceedings. Nevertheless, authors must indicate their preference for oral or poster presentation when submitting their paper.

Venue:

The conference will be held in Bruges (also called "Venice of the North"), one of the most beautiful medieval towns in Europe. Bruges can be reached by train from Brussels in less than one hour (frequent trains). Designated as the "Venice of the North", the city has preserved all the charms of the medieval heritage. Its centre, which is inscribed on the Unesco World Heritage list, is in itself a real open air museum.

The conference will be organized in a hotel located near the centre (walking distance) of the town. There is no obligation for the participants to stay in this hotel. Hotels of all levels of comfort and price are available in Bruges; there is a possibility to book a room in the hotel of the conference at a preferential rate through the conference secretariat. A list of other smaller hotels is also available.

The conference will be held at the Novotel hotel, Katelijnestraat 65B, 8000 Brugge, Belgium.

Proceedings and journal special issue:

The proceedings will include all communications presented to the conference (tutorials, oral and posters), and will be available on-site. Extended versions of selected papers will be published in the Neurocomputing journal (Elsevier).

Call for contributions:

Prospective authors are invited to submit their contributions before November 30, 2011. The electronic submission procedure is described on the ESANN portal http://www.esann.org/.

Authors must also commit themselves that they will register to the conference and present the paper in case of acceptation of their submission (one paper per registrant). Authors of accepted papers will have to register before February 29, 2012; they will benefit from the advance registration fee. The ESANN conference applies a strict policy about the presentation of accepted papers during the conference: authors of accepted papers who do not show up at the conference will be blacklisted for future ESANN conferences, and the lists will be communicated to other conference organizers.

Deadlines:

Submission of papers	November 30, 2011
Notification of acceptance	January 23, 2012
ESANN conference	April 25-27, 2012

Conference secretariat:

E-mail: esann@dice.ucl.ac.be, esann@uclouvain.be
http://www.esann.org
http://www.dice.ucl.ac.be/esann

ICCNS2012

16th International Conference on Cognitive and Neural Systems

May 30 – June 1, 2012
Boston University, Boston, USA
http://cns.bu.edu/cns-meeting/conference.html

Sponsored by the Boston University Center for Adaptive Systems, Center for Computational Neuroscience and Neural Technology (CompNet), and Center of Excellence for Learning in Education, Science, and Technology (CELEST), with financial support from the National Science Foundation

This interdisciplinary conference is attended each year by approximately 300 people from 30 countries around the world. As in previous years, the conference will focus on solutions to the questions:

How does the brain control behavior?
How can technology emulate biological intelligence?

The conference is aimed at researchers and students of computational neuroscience, cognitive science, neural networks, neuromorphic engineering, and artificial intelligence. It includes invited lectures and contributed lectures and posters by experts on the biology and technology of how the brain and other intelligent systems adapt to a changing world. The conference is particularly interested in exploring how the brain and biologically-inspired algorithms and systems in engineering and technology can learn. Single-track oral and poster sessions enable all presented work to be highly visible. Three-hour poster sessions with no conflicting events will be held on two of the conference days. Posters will be up all day, and can also be viewed during breaks in the talk schedule.

CALL FOR ABSTRACTS

* vision
* image understanding
* audition
* speech and language
* robotics
* neuromorphic VLSI
* sensory-motor control
* object recognition
* neural circuit models
* neural system models
* unsupervised learning
* supervised learning
* reinforcement and emotion
* industrial applications
* cognition, planning, and attention
* spatial mapping and navigation
* mathematics of neural systems
* hybrid systems (fuzzy, evolutionary, digital)

Contributed abstracts must be received, in English, by January 31, 2012. Email notification of acceptance will be provided by February 29, 2012. A meeting registration fee must accompany each abstract. The fee will be refunded if the abstract is not accepted for presentation. Fees of accepted abstracts will be returned upon written request only until April 13, 2012.

Abstracts must not exceed one 8.5"x11" page in length, with 1" margins on top, bottom, and both sides in a single-column format with a font of 10 points or larger. The title, authors, affiliations, surface, and email addresses should begin each abstract. A separate cover letter should include the abstract title; name and contact information for corresponding and presenting authors; requested preference for oral or poster presentation; and a first and second choice from the topics above, including whether it is biological (B) or technological (T) work [Example: first choice: vision (T); second choice: neural system models (B)].

Contributed talks will be 15 minutes long. Posters will be displayed for a full day. Overhead and computer projector facilities will be available for talks. Accepted abstracts will be printed in the conference proceedings volume. No extended paper will be required.

Abstracts should be submitted electronically as Word files to cindy@bu.edu using the phrase “16th ICCNS abstract submission” in the subject line or as paper hard copy (four copies of the abstract with one copy of the cover letter and the registration form) to Cynthia Bradford, Boston University, 677 Beacon Street, Boston MA 02215 USA. Fax submissions of the abstract will not be accepted.

ICNC2012/FSKD2012

8th International Conference on Natural Computation

9th International Conference on Fuzzy Systems and Knowledge Discovery

29-31 May 2012, Chongqing, China
http://icnc-fskd.cqupt.edu.cn

The 2012 8th International Conference on Natural Computation (ICNC'12) and the 2012 9th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD'12) will be jointly held from 29-31 May 2012, in Chongqing, China. Renowned as the Mountain City, Chongqing is a magnet for visitors from home and abroad for its cultural heritage and numerous attractions. There are many karst caves, hot springs, and gorges in the area. Major tourist spots in and near Chongqing include Dazu Grottoes

(rock carvings began in the Tang Dynasty 650 A.D.), Three Gorges, Jinyun Mountain Natural Reserve, Hongya Cave, Shibaozhai, Wulong Karst, etc.

All papers in the conference proceedings will be indexed by both EI Compendex and ISTP as with the past ICNC-FSKD conferences. Extended versions of selected best papers will appear in an ICNC-FSKD special issue of an SCI-indexed journal. ICNC'12-FSKD'12 is technically co-sponsored by the International Neural Network Society and the IEEE Circuits and Systems Society.

ICNC-FSKD is a premier international forum for scientists and researchers to present the state of the art of data mining and intelligent methods inspired from nature, particularly biological, linguistic, and physical systems, with applications to computers, circuits, systems, control, communications, and more. This is an exciting and emerging interdisciplinary area in which a wide range of theory and methodologies are being investigated and developed to tackle complex and challenging problems. The registration fee of US$400 includes proceedings, lunches, dinners, banquet, coffee breaks, and all technical sessions.

CIBCB2012

IEEE Symposium on Computational Intelligence in Bioinformatics and Computational Biology

May 9-12, 2012, San Diego, USA
http://www.cibcb.org/2012/

This symposium will bring together top researchers, practitioners, and students from around the world to discuss the latest advances in the field of Computational Intelligence and its application to real world problems in biology, bioinformatics, computational biology, chemical informatics, bioengineering and related fields. Computational Intelligence (CI) approaches include artificial neural networks and machine learning techniques, fuzzy logic, evolutionary algorithms and meta-heuristics, hybrid approaches and other emerging techniques.

Topics of interests include, but are not limited to:

- Gene expression array analysis
- Structure prediction and folding
- Molecular sequence alignment and analysis
- Metabolic pathway analysis
- DNA and protein folding and structure prediction
- Analysis and visualization of large biological data sets
- Motif detection
- Molecular evolution and phylogenetics
- Systems and synthetic biology
- Modelling, simulation and optimization of biological systems
- Robustness and evolvability of biological networks
- Emergent properties in complex biological systems
- Ecoinformatics and applications to ecological data analysis
- Medical imaging and pattern recognition
- Medical image analysis
- Biomedical data modelling and mining
- Treatment optimisation
- Biomedical model parameterisation
- Brain computer interface

The use of CI must play a substantial role in submitted papers. Submissions will be peer reviewed and accepted papers will be published in the conference proceedings and will be indexed in IEEE Xplore. Selected papers after a substantial extension will be considered to be published in a special issue of IEEE/ACM TCBB. One Best Paper Award and one Best Student Paper Award will be given.

Prospective authors are invited to submit papers of no more than eight (8) pages in IEEE conference format, including results, figures and references. Submission details can be found at: http://www.cibcb.org/2012/. For additional information contact the General Chair, Prof. Yaochu Jin, Department of Computing, University of Surrey, UK. Email: yaochu.jin@surrey.ac.uk.

Important dates

Special sessions proposals:	October 3, 2011
Paper submission deadline:	November 20, 2011
Paper acceptance:	February 19, 2012
Final paper submission:	March 18, 2012

Keynote Speech

"Using Bioinformatics and Systems Biology to Enable Early Stage Drug Discovery"
Prof. Philip E. Bourne, University of California San Diego

Organizing Committee

General Chair:	Yaochu Jin (UK)
Program Chair:	Alioune Ngom (Canada)
Technical Co-Chairs:	Dan Ashlock (Canada)
	Xuewen Chen (USA)
	Sheridan Houghten (Canada)
	Jaap Kaandorp (NL)
	Natalio Krasnogor (UK)
	Emma Laing (UK)
	Mihail Popescu (USA)
Finance Chair:	Steven Corns (USA)
Local Arrangements Chair:	Gary Fogel (USA)
Special Session Chair:	Jonathan Chan (Thailand)
Tutorial Chair:	Yuehui Chen (China)
Proceedings Chair:	Yonghong Peng (UK)
Publicity Chair:	Yanqing Zhang (USA)
Competition Chairs:	Dan Ashlock (Canada)
	Steven Corns (USA)
Web Chair:	Wissam Albukhanajer (UK)

2012 IJCNN International Joint Conference on Neural Networks

The annual International Joint Conference on Neural Networks (IJCNN) will be held jointly with the IEEE International Conference on Fuzzy Systems (FUZZIEEE) and the IEEE Congress on Evolutionary Computation (IEEE CEC) as part of the 2012 IEEE World Congress on Computational Intelligence (IEEE WCCI), June 10-15, 2012, Brisbane Convention & Exhibition Centre, Brisbane, Australia. Cross-fertilization of the three technical disciplines and newly emerging technologies is strongly encouraged.

IJCNN Organization Committee

Conference Chair

Cesare Alippi, Italy

Program Chair

Kate Smith-Miles, Australia

Technical Co-Chairs

Derong Liu, China

Pablo A.Estévez, Chile

Kay Chen Tan, Singapore

James Tin-Yau Kwok, Hong Kong

Ke Chen, UK

Robert Kozma, USA

Neuroscience liaison

Ali Minai, USA

Special Sessions Chair

Brijesh Verma, Australia

Tutorial Chair

Haibo He, USA

Competitions Chair

Sung-Bae Cho, Korea

Call for Contributed Papers

The annual IJCNN is the premier international conference in the field of neural networks. It covers all topics in neural networks including, but is not limited to:

- **Neural network theory & models**
- **Learning and adaptation**
- **Cognitive models**
- **Brain-machine interfaces**
- **Neural control**
- **Evolutionary neural systems**
- **Neurodynamics and complex systems**
- **Neuroinformatics**
- **Neural hardware**
- **Neural network applications**
- **Neuroengineering**
- **Computational neuroscience**
- **Pattern recognition**
- **Machine vision and image processing**
- **Collective intelligence**
- **Hybrid systems**
- **Self-aware systems**
- **Data mining**
- **Sensor networks and intelligent systems**
- **Applications**
- **Computational biology**
- **Bioinformatics**

IJCNN 2012 will feature a world-class conference that aims to bring together researchers and practitioners in the field of neural networks and computational intelligence from all around the globe. Technical exchanges within the research community will encompass keynote lectures, special sessions, tutorials and workshops, panel discussions as well as poster presentations. In addition, participants will be treated to a series of social functions, receptions, and networking to establish new connections and foster everlasting friendship among fellow counterparts.

Prospective authors are invited to contribute high-quality papers to IJCNN 2012. All papers are to be submitted electronically through the IEEE WCCI 2012 website http://www.ieee-wcci2012.org/.

For IJCNN inquiries please contact Conference Chair: Cesare Alippi at cesare.alippi@polimi.it
For Program inquiries please contact Program Chair: Kate Smith-Miles at kate.smith-miles@sci.monash.edu.au

Call for Special Sessions

The IJCNN 2012 Program Committee solicits proposals for special sessions within the technical scopes of the Congress. Special sessions, to be organized by international recognized experts, aim to bring together researchers in special focused topics. Papers submitted for special sessions are to be peer-reviewed with the same criteria used for the contributed papers. Proposals should include the session title, a brief description of the scope and motivation, biographic and contact information of the organizers. Researchers interested in organizing special sessions are invited to submit formal proposal to the Special Session Chair:

Brijesh Verma at b.verma@cqu.edu.au.

Call for Tutorials

IJCNN 2012 will also feature pre-Congress tutorials, covering fundamental and advanced neural network topics. A tutorial proposal should include title, outline, expected enrollment, and presenter/organizer biography. We invite you to submit proposals to the Tutorial Chair:

Haibo He at he@ele.uri.edu

Call for Competitions

IJCNN 2012 will host competitions to stimulate research in neural networks, promote fair evaluations, and attract students. The proposals for new competitions should include descriptions of the problems addressed, motivations, expected impact on neural networks and machine learning, and established baselines, schedules, anticipated number of participants, and a biography of the main team members. We invite you to submit proposals to the Competitions Chair:

Sung-Bae Cho at sbcho@yonsei.ac.kr.

General Enquires for IEEE WCCI 2012 should be sent to the General Chair:
Hussein Abbass at hussein.abbass@gmail.com

Important Dates

Competition proposals submission deadline
October 17, 2011

Special sessions proposal submission deadline
November 21, 2011

Special session decision notification
November 28, 2011

Paper submission deadline
December 19, 2011

Tutorial and Workshop proposal submission deadline
January 16, 2012

Tutorial and Workshop decision notification
January 23, 2012

Paper acceptance notification date
February 20, 2012

Final paper submission deadline
April 2, 2012

Early registration
April 2, 2012

Conference dates
June 10-15, 2012